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Information-based maintenance optimization with focus on predictive maintenance

Adriaan Van Horenbeek

Dissertation presented in partial fulfillment of the requirements for the degree of Doctor in Engineering

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Supervisory Committee:
Prof. dr. ir. H. Hens, chair
Prof. dr. ir. L. Pintelon, supervisor
Prof. dr. ir. J.R. Duflou
Prof. dr. ir. P. Sas

Prof. dr. ir. P. Dehombreux
(Université de Mons)
Prof. dr. P.A. Scarf
(University of Salford)
Prof. dr. ir. L.A.M. van Dongen
(Universiteit Twente)

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Dankwoord

"Success consists of going from failure to failure without loss of enthusiasm." - Winston Churchill

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> "Now this is not the end. It is not even the beginning of the end. But it is, perhaps, the end of the beginning." - Winston Churchill

Adriaan

Abstract

This dissertation presents an information-based maintenance optimization methodology for physical assets; with focus on, but not limited to, predictive maintenance (PdM). The overall concept of information-based maintenance is that of updating maintenance decisions based on evolving knowledge of operation history and anticipated usage of the machinery, as well as the physics and dynamics of material degradation in critical machinery components. Within this concept, predictive maintenance is a maintenance policy that specifically uses predictions of component remaining useful life (RUL) to dynamically schedule maintenance activities.

Analysis of the available information-based maintenance methodologies and e-maintenance standards identified the development of advanced maintenance policies like predictive maintenance as the most important challenge. Generally speaking, within e-maintenance the sensor module, the signal-processing module, the condition monitoring module and the diagnostic model can all be (partially) developed using standard means and models. However, this is currently not the case for the decision support modules. Moreover, the evolution of maintenance is not solely based on technical but rather on techno-economic considerations. The right maintenance decision making structure should be in place to fully exploit the potential of these new emerging technologies. Therefore, decision support models and tools for predictive maintenance performance evaluation and optimization are developed in this thesis. Hence, a detailed study on the business economics related to the implementation of an information-based/predictive maintenance policy is performed. Predictive maintenance models for long-term performance evaluation, real-time and dynamic decision making and a combination of both are developed. As such contributions are made towards (i) the development of an imperfect condition monitoring system (CMS) model, (ii) predictive maintenance models incorporating product quality and production capacity and (iii) a dynamic predictive maintenance policy for complex dependent multi-component systems. These models provide maintenance decision support in order to take cost-effective decisions based on predictive maintenance information. Moreover, they provide sound business insight for the justification of PdM and as such assist to determine the cases in which PdM is expected to be very beneficial, beneficial, neutral or possibly too expensive. Furthermore, the effect of predictive maintenance information on inventory management decisions is studied.

The major contribution of this dissertation lies within the development of predictive maintenance models. However, contributions to other problems within maintenance management, like (i) the urge for more application based maintenance optimization, (ii) the limited scope with regard to maintenance objectives and criteria and (iii) the availability of maintenance data, are made. As such most of the developed models are applied to real-life case studies to illustrate their applicability in an industrial setting. A methodology, based on the analytic network process (ANP), is developed to select and prioritize business specific maintenance objectives and criteria. And finally, the developed models possess the capability to solve the data problem by providing the maintenance decision maker the right information at the right time to make the right maintenance decision.

Beknopte samenvatting

Dit proefschrift ontwikkelt een informatiegebaseerde methodologie voor onderhoudsoptimalisatie van machinecomponenten. Hierbij ligt de focus op predictief onderhoud (PdM). Het concept van informatiegebaseerd onderhoud kan gedefinieerd worden als: het actualiseren van onderhoudsbeslissingen gebaseerd op de evolutie van kennis omtrent de werkingshistorie en geanticipeerd gebruik van een machine, evenals de degradatie van kritische machinecomponenten. Binnen dit concept kan predictief onderhoud gedefinieerd worden als een onderhoudspolitiek waarbij een voorspelling van de resterende levensduur van componenten (i.e. *remaining useful life (RUL)*) wordt gebruikt om op een dynamische wijze onderhoudsactiviteiten te plannen.

Analyse van de reeds beschikbare informatiegebaseerde onderhoudsmethodologieën en *e-maintenance* standaarden leert dat de grootste uidaging ligt in de ontwikkeling van geavanceerde onderhoudspolitieken zoals predictief onderhoud. In het algemeen kunnen binnen *e-maintenance* de modules voor sensoren, signaalverwerking, conditiebewaking en diagnostiek (gedeeltelijk) ontwikkeld worden aan de hand van standaardmodellen. Dit is momenteel echter niet het geval voor de beslissingsondersteunende modellen. Bovendien steunt de evolutie van onderhoud niet enkel op technische ontwikkelingen maar veeleer op techno-economische overwegingen. De juist beslissingsstructuur moet aanwezig zijn om het volledige potentieel van deze opkomende technologie te benutten. Daarom zijn er in deze thesis beslissingsondersteunende modellen voor de evaluatie en optimalisatie van de performantie van predictief onderhoud ontwikkeld. Bijgevolg is er een gedetailleerde studie uitgevoerd met betrekking tot de economische aspecten die gekoppeld zijn aan de implementatie van een informatiegebaseerde/predictieve onderhoudspolitiek. Zo zijn er predictieve onderhoudsmodellen ontwikkeld voor lange termijn evaluatie, dynamische beslissingsondersteuning evenals een combinatie van beide. Zodanig wordt er een bijdrage geleverd tot (i) de ontwikkeling van een model van een niet perfect conditiebewakingssysteem, (ii) predictieve onderhoudsmodellen waarin productkwaliteit en productiecapaciteit in rekening worden gebracht en (iii) een

dynamisch predictief onderhoudsmodel voor een complex systeem met meerdere afhankelijke componenten. Deze modellen verstrekken beslissingsondersteuning binnen onderhoudsmanagement om tot kosteneffectieve beslissingen gebaseerd op predictieve informatie te komen. Bovendien verstrekken deze duidelijk inzicht in de meerwaarde en economische rechtvaardiging van predictief onderhoud. Op deze manier assisteren ze om te bepalen in welke gevallen predictief onderhoud verondersteld wordt om zeer voordelig, voordelig, neutraal of zelfs te duur te zijn. Verder wordt ook het effect van het gebruik van predictieve informatie op de voorraadbeslissingen bestudeerd.

De belangrijkste contributie van dit proefschrift ligt in de ontwikkeling van predictieve onderhoudsmodellen. Het is echter zo dat er ook bijdragen gemaakt zijn tot andere geïdentificeerde problemen binnen onderhoudsmanagement, dewelke als volgt beschreven kunnen worden: (i) er is een duidelijke behoefte aan meer toegepaste onderhoudsoptimalisatie en praktisch bruikbare modellen, (ii) de *scope* van de gebruikte onderhoudsobjectieven is gelimiteerd en (iii) de beschikbaarheid van onderhoudsdata. Dusdanig zijn de meeste van de ontwikkelde modellen toegepast op een werkelijke industrïele case studie om hun toepasbaarheid aan te tonen in een industriële context. Een methodologie, gebaseerd op *analytic network process (ANP)*, is ontworpen om onderhoudsobjectieven te selecteren en rangschikken gegeven een welbepaalde bedrijfsomgeving. Tenslotte, wordt een bijdrage geleverd tot het oplossen van het probleem omtrent de beschikbaarheid van onderhoudsdata. Dit door de onderhoudsbeslisser de juiste informatie op het juiste moment te verschaffen om de juiste onderhoudsbeslissing te maken.

Abbreviations

A	Availability
ABAO	As Bad As Old
AGAN	As Good As New
AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
CBM	Condition-Based Maintenance
CI	Consistency Index
CM	Condition Monitoring
CM	Corrective Maintenance
CMMS	Computerized Maintenance Management System
CMS	Condition Monitoring Systems
CR	Consistency Ratio
CRD	Capital Replacement Decisions
EI	Environmental Impact
F&T	Functional and Technical Aspects
FMEA	Failure Mode and Effect Analysis
GA	Genetic Algorithm
I	Inventory
ICT	Information and Communication technology
IT	Information Technology
JCF	Joint Cost Function
KKT	Karush-Kuhn-Tucker

L	Logistics
LCC	Life Cycle Cost
LCCA	Life Cycle Cost Analysis
LCO	Life-Cycle Optimization
M	Maintainability
MB	Maintenance Budget
MC	Maintenance Costs
MPI	Maintenance Performance Indicators
MPM	Maintenance Performance Measurement
MQ	Maintenance Quality
MV	Maintenance Value
OEE	Overall Equipment Effectiveness
OEM	Original Equipment Manufacturer
OQ	Output Quality
OSA-CBM	Open System Architecture for Condition-Based Maintenance
P	Productivity
P&E	People and Environment
PDL	Plant Design Life
PdM	Predictive Maintenance
PHM	Proportional Hazard Model
PM	Personnel Management
PM	Preventive Maintenance
POM	Prognostics for Optimal Maintenance
PSS	Product Service System
R	Reliability
RCM	Reliability Centered Maintenance
REML	Restricted Maximum Likelihood
RI	Random Index
ROI	Return On Investment
RPN	Risk Priority Number
RQ	Research Question
RUL	Remaining Useful Life
S	Support
SRH	Safety Risk Health
TBM	Time-Based Maintenance

TPM	Total Productive Maintenance
TTR	Time To Repair
UBM	Use-Based Maintenance
VFFS	Vertical Form Fill and Seal
WACC	Weighted Average Cost of Capital

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Chapter 1

Introduction

1.1 The importance of asset and maintenance management

In the face of current global competition and increasing demands from stakeholders, there is a distinct need to improve manufacturing performance. Due to widespread automation, the implementation of advanced manufacturing technologies and the high capital tied up in production equipment, the importance of asset and maintenance management within manufacturing is ever increasing (Tsang 2002). Moreover, the economic downturn and the dynamic business environment drive companies to seek more efficient and effective maintenance.

The huge cost and risks related to improper maintenance have been both observed and documented in industry (Holmberg et al. 2010). Moreover, according to the study of Al-Najjar and Pehrsson (2005) maintenance is directly linked to competitiveness and profitability and thus to the future of a company. The competitiveness and performance of manufacturing companies depend on the availability, reliability and productivity of their production equipment. Furthermore, the economic factors related to maintenance such as maintenance direct cost, production losses and maintenance investments have a major influence on a big share of a company's income (Al-Najjar 2007). This view supports the study of Mckone and Weiss (1998), as the authors mention that the amount of money DuPont spent company-wide on maintenance was roughly equal to its net income. It should be noted that maintenance forms an integral part of manufacturing and its price tag can indicate its significance to companies.

Latino (1999) conducted a study that indicates that the United States spend well over \$300 billion on plant maintenance and operations. An estimated 80% of these costs are expended to correct chronic failures of machinery. Eliminating these failures can reduce maintenance costs by 40% up to 60%. Furthermore, these possible savings can be realized without major restructuring, employee layoffs or sacrifice of product quality (Latino 1999). However, it does require changes in the current mindset on how to maintain and operate machines and entire facilities. According to Robertson and Jones (2004) maintenance budgets range from 2 to 90 % of the total plant operating budget, with the average being 20,8% (Jardine and Tsang 2006). From all these figures it can be reasoned that maintenance represents a major cost item in equipment-intensive industrial operations. However, focus should not only be on costs as maintenance also generates business value. Recently, companies recognize that maintenance can provide value to their business, while in the past maintenance was only seen as a cost factor, having a negative effect on the productivity of the company. This recognition has led to a drastic change of perception on maintenance over the past decades, evolving from a "necessary evil" to a "value adding" activity. This makes maintenance an investment opportunity to be optimized, not a cost to be minimized. This can be achieved by making the right and opportune maintenance decisions based on the available information. Decision models can help companies to exploit and determine the value of maintenance. Which brings us directly to the major subject of this dissertation.

Huge maintenance budgets are still spent by industrial companies nowadays, however, new technologies (e.g. IT technologies, diagnostics, prognostics and e-maintenance) are emerging which possess the potential to reduce maintenance costs and increase maintenance efficiency, and consequently generate business value. However, care should be taken, as it is clear that the evolution of maintenance is not solely based on technical but rather on techno-economic considerations. Implementation of these technologies does not guarantee any value without the right decision making structure and business economics in place, as maintenance cannot be managed as a purely technical or technological function only (Pintelon and Van Puyvelde 2006).

1.2 Defining asset and maintenance management

Many definitions on *maintenance* exist, but when considering the bottom line, it can be best defined as a set of activities required to keep equipment, installations and other physical assets in the desired operating condition or to restore them to this condition (Pintelon and Van Puyvelde 2006). However, this definition might be too simple and narrow to define maintenance in all its complexities, therefore *maintenance management* is defined. Recently, on an even higher and more complex management level *asset management* is defined within industrial companies and academic literature. Asset management, even more profound than maintenance management, focuses on the entire life cycle of an asset, including strategy, risk measurement, safety and environment and human factors (Amadi-Echendu et al. 2007). The different types of assets within an organization are defined as: financial assets, physical assets, human assets, information assets and intangible assets. The focus of this dissertation lies within physical asset management. A publicly available specification for the optimized management of physical assets published by the British Standards Institution (PAS 55:2008) defines physical asset management as follows (Figure 1.1):

> "*Asset management can be defined as the systematic and coordinated activities and practices through which an organization optimally and sustainably manages its assets and asset systems, their associated performance, risks and expenditures over their life cycles for the purpose of achieving its organizational strategic plan.*" (PAS 55:2008)

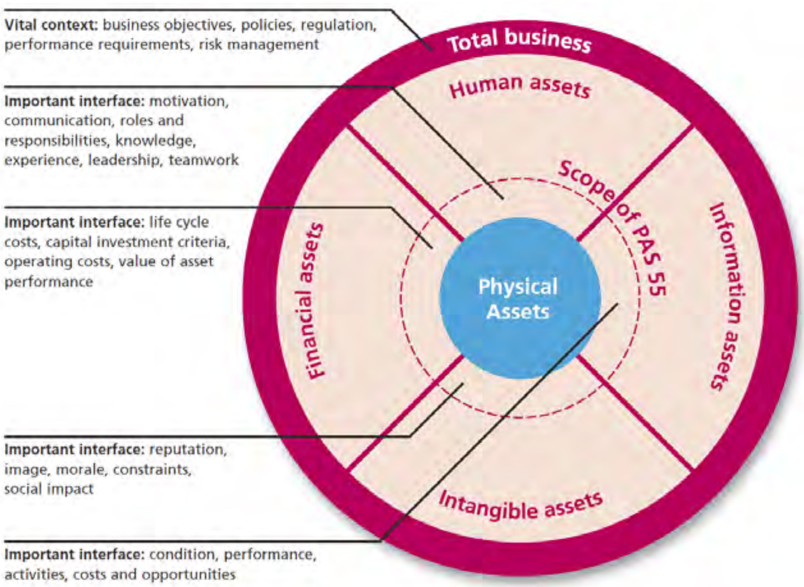

Figure 1.1: Focus and business context of physical asset management in relation to other categories of assets (PAS 55:2008).

Physical asset management describes a systematic approach around whole life cycle management of assets from concept to disposal; including acquisition, utilization, maintenance and renewal or disposal of the manufacturing equipment (Campbell et al. 2011). The scope of this dissertation is on management of the maintenance function within the life cycle as according to the statements in Section 1.1 major potential for improvement is still present within maintenance management. Although maintenance management is the major topic some side steps will be made regarding the utilization and renewal of physical assets.

According to the European standard (EN 13306:2010), maintenance management can be defined as: "all activities of the management that determine the maintenance objectives, strategies and responsibilities, and implementation of them by such means as maintenance planning, maintenance control, and the improvement of maintenance activities and economics". A similar definition of maintenance management is given by Crespo Marquez (2007) as follows:

> *"All the activities of the management that determine the maintenance objectives or priorities (defined as targets assigned and accepted by the management and maintenance department), strategies (defined as a management method in order to achieve maintenance objectives), and responsibilities and implement them by means such as maintenance planning, maintenance control and supervision, and several improving methods including economical aspects in the organization."*

Based on these definitions it is possible to derive the major components or steps to follow in order to develop a maintenance management methodology:

1. Determination and measurement of maintenance objectives.
2. Maintenance strategies and policies definition and selection according to performance measures.
3. Maintenance planning, control and continuous improvement.

1.3 Maintenance evolution

The last decades maintenance practice has gone through a process of change due to the increasing awareness of the importance of maintenance management (See Figure 1.2 for an overview of the described maintenance policies). In the 1950's corrective or reactive maintenance (run-to-failure) was the predominant maintenance policy. In the 1960's preventive maintenance (time- or use-based maintenance) became popular. Regular component replacements were scheduled in order to try to avoid any possible - unscheduled - failure regardless of the health status of a physical asset. In the second half of the 1980's more and more companies were wondering whether they were not overdoing maintenance by e.g. replacing components with potentially interesting remaining life time. Therefore, condition monitoring and diagnostic technologies were developed and consequently condition-based maintenance (CBM) emerged. Condition-based maintenance is defined according to the European standard (EN 13306:2010) as follows: "preventive maintenance which includes a combination of condition monitoring and/or inspection and/or testing, analysis and the ensuing maintenance actions". In other words, the appropriate maintenance actions are triggered based on the condition monitoring information available from the past up until the decision time. In this way, CBM attempts to avoid unnecessary maintenance activities by triggering these actions only when there is evidence of deterioration or abnormal behavior. The idea that by monitoring - continuously or intermittently – the status of a machine or some of its components can be used to determine whether maintenance is yet needed, received quite some interest (Jardine and Tsang 2006; Jardine, D. Lin, et al. 2006; Van Horenbeek, Pintelon, and Muchiri 2010). In the beginning this seemed to be reserved for the high risk industries, but as it became cheaper it found its way to the industry at large. Recently, prognostics, which deals with fault prediction before it occurs, made its introduction into maintenance management. Fault prediction determines whether a fault is impending and estimates how soon and how likely a fault will occur (Jardine, D. Lin, et al. 2006). Prognostics is a prior event analysis rather than diagnostics which is a posterior event analysis. A maintenance policy incorporating prognostics into the decision process is defined as a predictive maintenance policy (PdM). Predictive maintenance can be defined as: "condition-based maintenance carried out following a forecast (i.e. remaining useful life (RUL)) derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item" (EN 13306:2010). This means that, compared to CBM, PdM incorporates more information into the maintenance decision process as information on future machine or component degradation, in the form of their remaining useful life by prognostics, is taken into account.

The development of the communication and information technologies, in order to support diagnostics, prognostics and corresponding advanced maintenance policies within maintenance, has allowed the emergence of the concept of e-maintenance. E-maintenance integrates existing telemaintenance principles with web services and modern e-collaboration principles that allow to share pertinent knowledge at the right place and time, in order to take the right maintenance decisions based on the available information (Muller et al. 2008). E-maintenance fully exploits the possibilities of condition monitoring coupling it with high tech ICT and expertise/intelligence. It also opens the door to the next generation of maintenance, the proactive maintenance, which focuses on

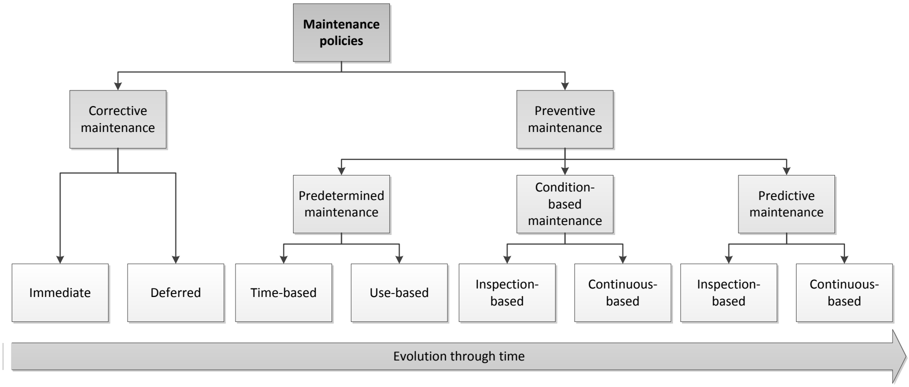

Figure 1.2: Maintenance policies overview.

designing-out (recurrent) problems (Pintelon and Van Puyvelde 2006). Defining e-maintenance is rather difficult as according to different authors it can be defined as a maintenance strategy, maintenance plan, maintenance type as well as maintenance support. However, Muller et al. (2008) tries to combine these different views and comes to the following definition of e-maintenance:

> *"Maintenance support which includes the resources, services and management necessary to enable proactive decision process execution. This support includes e-technologies (i.e. ICT, web-based, wireless, infotronics technologies) but also, e-maintenance activities (operations or processes) such as e-monitoring, e-diagnosis, e-prognosis, etc."*

Many e-maintenance standards, platforms, processes and implementations are discussed in literature. For an extensive overview of these publications the interested reader is referred to the work of Muller et al. (2008). All publications mention the importance of predictive maintenance within the concept of e-maintenance, which makes it self-evident that these two are strongly interconnected. When looking into more detail into the defined standards of e-maintenance, it can be concluded that the sensor module, the signal-processing module, the condition monitoring module and the diagnostic model can all be (partially) developed using standard means and models. However, according to Muller et al. (2008) this is not the case for the prognostics and decision support modules. Furthermore, Liyanage et al. (2009) mention the development of advanced maintenance policies like predictive maintenance as one of the most important challenges of e-maintenance applications. In the last couple of years, many papers discuss the ability to predict component degradation and corresponding remaining useful life based on condition monitoring information (Jardine, D. Lin, et al. 2006; Heng et al. 2009; Sikorska et al. 2011). However, few publications appear in literature that investigate the economic feasibility of predictive maintenance policies, which are based on these prognostic models and solutions. Maintenance is not just a technical problem but also an economic problem. Business economics are important, as maintenance cannot be managed as a purely technical or technological function only (Pintelon and Van Puyvelde 2006). It is clear that the newly developed maintenance technologies will not be effective without excellent management. Therefore, there is a clear need for maintenance decision support systems and models in order to take cost-effective decisions based on prognostic information.

1.4 General problems within maintenance management

Despite many technological and management advances happened within maintenance, there are still some major issues identified in literature that remain unresolved or unaddressed throughout the last decades, next to the issues discussed in Section 1.3 within predictive maintenance. A short overview of these is given here, and a more detailed description can be found in Chapter 2.

The first one is the limited scope that is taken with regard to maintenance objectives, as in most of the models a cost optimization approach is taken (Van Horenbeek, Pintelon, and Muchiri 2010). Moreover, no justification on the used maintenance objectives is given in the form of answering the question: "are these the real business specific maintenance objectives?".

Many models to determine optimal maintenance policies appear in literature. However, more application oriented research is necessary according to Dekker (1995b), as currently the gap between academic models and application in a business context is still the biggest problem encountered within maintenance management and optimization. Generally, case studies are not well represented within the available literature on maintenance management and optimization (Nicolai and Dekker 2007). There is a clear need for a shift from theoretical research to applied research (i.e. develop models applicable to real life case studies) within maintenance optimization (Scarf 1997; Garg and Deshmukh 2006).

Directly linked to the few maintenance case studies that appear in literature is the lack of good maintenance data. As Dekker (1996) states, data availability is often seen as the biggest obstacle to overcome to close the gap between maintenance optimization models and real life case studies. The necessary data can be categorized under three main headings, namely failure data, operating data and cost data (Van Horenbeek, Pintelon, and Muchiri 2010). However, most maintenance information systems mainly contain accounting information, which is not valuable for maintenance optimization, rather than maintenance event and cost data. Moreover, it is relatively easy to quantify or register direct maintenance costs (e.g. component cost), but indirect maintenance costs (e.g. due to accelerated wear) are much more difficult to determine. There is a clear need for the existence of a maintenance database that provides reliable information for maintenance analysis (Caldeira Duarte et al. 2013). The introduction of the concept of e-maintenance has according to several authors (Muller et al. 2008) the potential to solve the maintenance data problem.

1.5 Scope

The delineation of the scope of this dissertation is based on the descriptions given in Sections 1.2 - 1.4. The main scope of this thesis is on physical asset management, and more specifically physical maintenance management. This means that only maintenance management for physical production equipment is considered and that not the entire life cycle of the equipment is considered (i.e. physical asset management), but rather only the maintenance stage within the life cycle. Although, some side steps are made towards inventory management as inventory is directly coupled to maintenance management within the value chain. Special focus is on, but not limited to, the performance evaluation and optimization of predictive maintenance without development of the condition monitoring or prognostic models used for remaining useful life prediction themselves. In this way it is assumed that the condition monitoring and prognostic tools and models are available from other studies or company set-ups. Accordingly, two limitations on the scope can be defined as follows:

> *Research scope limitation 1*: maintenance management for physical assets.
>
> *Research scope limitation 2*: predictive maintenance performance evaluation and optimization without development of condition monitoring or prognostic tools and models.

1.6 Research questions

The overall research goal of this dissertation is to **develop an information-based maintenance methodology with focus on predictive maintenance policy development and corresponding performance determination and optimization**. Where the predictive maintenance policy is defined as a maintenance policy that uses predictions on remaining useful life in a dynamic way to optimally schedule maintenance activities. The definition of Muller et al. (2008) for information-based maintenance, which clearly highlights the major objective of this dissertation, is adopted as follows:

> *"The overall concept of information-based maintenance is that of updating decisions for inspection, repair, and maintenance scheduling based on evolving knowledge of operation history and anticipated usage of the machinery, as well as the physics and dynamics of material degradation in critical components."*

Furthermore, the business economics related to the implementation of an information-based/predictive maintenance policy are studied in detail. In order to handle the issues mentioned in Section 1.4 special attention is paid to these throughout the entire dissertation. In fact considering these issues can already be seen as one of the major contributions of this thesis. As such all developed models within the framework of this dissertation are applied and validated on real life case studies. By doing so we clearly address the problem of applicability of the developed maintenance optimization models like stated in Section 1.4. Moreover, all these case studies consider multiple and different maintenance objectives and throughout the execution of these case studies special attention is paid to data collection and analysis. Since real life case studies are considered we gain insight into maintenance data and it is possible to determine which data, and in which format, should be collected to be able to build reliable maintenance models. In this way all issues mentioned in Section 1.4 are considered.

The main research goal can be further subdivided into three research questions, according to the derived steps for the development of a maintenance management methodology, as defined in Section 1.2. By linking all research questions an information-based maintenance methodology with focus on predictive maintenance is developed, but the methodology (in parts or its entirety) is applicable to other maintenance policies too.

1.6.1 First research question (RQ1)

The first research goal addresses the limited scope of maintenance objectives used in maintenance management (Section 1.4). A maintenance objective is defined as a target assigned and accepted for the maintenance activities (EN 13306:2010). These targets may include for example availability, cost reduction, product quality, environment preservation or safety. The first research goal is to develop a methodology/model that derives and prioritizes business specific maintenance objectives and by doing so answers the following research question:

> *"How to determine and prioritize business specific maintenance objectives which can be used for maintenance performance measurement (MPM), management and optimization?"*

1.6.2 Second research question (RQ2)

For preventive maintenance optimization (e.g. determining the best frequency of component repair or replacement), a vast literature is available covering simple up to complex configurations (Cho and Parlar 1991; Dekker 1995b; Jardine, D. Lin, et al. 2006; McCall 1965; Nakagawa 2005; Pham and H. Wang 1996; Pierskalla and Voelker 1976; Scarf 1997; Sherif and M. L. Smith 1981; Valdez-Flores and Feldman 1989; Van Horenbeek, Pintelon, and Muchiri 2010; H. Wang 2002). Although everybody seems convinced that condition monitoring is more interesting than preventive maintenance from the business point of view, little or no research has been done to develop models for return on investment (ROI) analysis for predictive maintenance. Companies often engage in PdM based on "educated guesses". The mathematical model to be developed here should provide sound business insight for justification of PdM and in such a way should help to select the cases in which PdM is expected to be very beneficial, beneficial, neutral or – possibly – too expensive. Again the business economics behind the technology should be considered, as it does not necessarily mean that the most advanced technological solution is also the best. For some equipment (e.g. random failures) failure-based maintenance could well be the best maintenance policy to implement. Furthermore, a predictive maintenance model should not only be able to determine the long-term performance of PdM, but it should also assist in real-time scheduling and decision making by dynamically updating maintenance schedules and actions based on newly available information like for example remaining useful life. This supports the view of Dekker (1996) who states that a general model structure is necessary. Moreover, the model should be able to cope with complex multi-component systems, taking into account for example component interactions, as in this way it addresses the problem of applicability of the developed model in a real life business environment (Section 1.4). Thus, the second research goal can be formulated as follows:

> *"Determine the added value of predictive information on component degradation in the form of remaining useful life (i.e. information-*

based) in maintenance decision making by developing and optimizing a dynamic predictive maintenance policy (PdM) for complex multi-component systems that can be used for both long-term performance evaluation of PdM, as for real-time and dynamic maintenance decision making."

1.6.3 Third research question (RQ3)

It is generally perceived that the introduction of PdM not only adds value to maintenance operations, but also to other elements within the value chain of a company, although this is never quantified in detail. The one that is particularly studied within the framework of this dissertation is inventory management. PdM can possibly generate value within inventory management due to the better predictability of spare part demand (i.e. this is directly determined by the adopted maintenance policy), which reduces stock outs and holding costs.

"How and how much value will predictive maintenance generate in the entire value chain, specifically looking to inventory management?"

1.7 Structure of the dissertation and main contributions

This section gives an overview of the overall structure of the dissertation along with the main research contributions discussed and presented in the respective chapter. As can be seen in Figure 1.3 the dissertation consists of six chapters, next to the introduction and conclusions. All chapters are categorized according to the appropriate research question they address. Moreover, the chapters are composed in such a way that they can all be read separately and independently from each other.

Although a general overview of the evolution of maintenance is given and the major research questions are already formulated in the introduction, a detailed literature review is given in **Chapter 2**. The presented literature review has a specific focus on the defined research questions and maintenance methodology. In this way it is not our purpose to give an exhaustive list or overview of all previously published papers. Instead we highlight the essential publications and derive important parameters for maintenance management and optimization within the scope of this dissertation. The target of this chapter is to collect essential published information that is relevant to answer the posed research

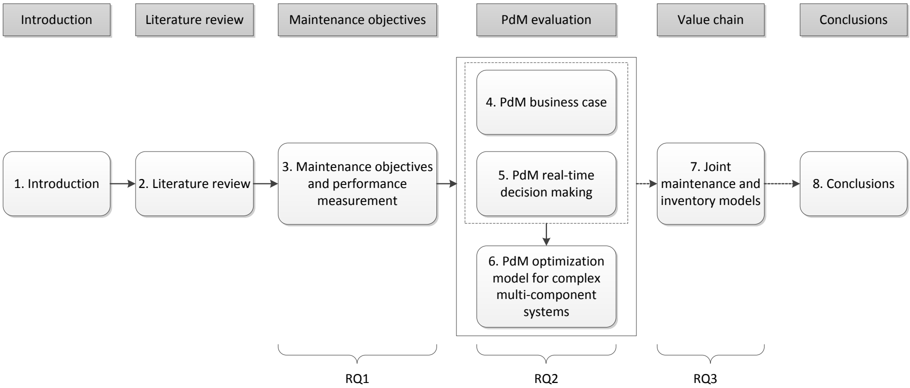

Figure 1.3: Dissertation structure overview.

questions. More specific literature relevant for a separate chapter is discussed in detail in the respective chapters.

Chapter 3 presents a developed methodology for the derivation of maintenance objectives and criteria according to the business context of a company. Moreover, it is extended to incorporate maintenance performance measurement and applied to several use cases. This chapter directly addresses RQ1.

Chapters 4 to 6 are classified under the same category and present models applicable to RQ2. A theoretical model for the performance evaluation of imperfect condition-based and predictive maintenance on the long-term is discussed in Chapter 4. In other words, this type of model determines the added value of condition monitoring information in maintenance decision making and by doing so it answers the question to invest or not in condition monitoring technology. The model is specifically applied and validated on a case study of a wind turbine gearbox. The major advantage of the presented model is that no real condition monitoring data is necessary, however this also means that no maintenance plan can be determined. On the other hand, chapter 5 presents three optimization models for real-time optimal maintenance decision making and planning based on condition monitoring and corresponding prognostic information for three specific case studies. However, for these models condition monitoring information is a prerequisite, which makes it rather difficult to determine their long-term performance. As the second research goal is to develop a dynamic predictive maintenance policy for complex multi-component systems that can be used for both long-term performance evaluation of PdM, as for real-time and dynamic maintenance decision making; a dynamic predictive maintenance policy is presented in Chapter 6 that combines the advantages of both models presented in Chapter 4 and 5. As such, models for long-term performance evaluation of PdM (Chapter 4), models for real-time decision making within PdM (Chapter 5) as a combination of both (Chapter 6) are developed in this dissertation. By adopting these models it is possible to derive the added value of PdM compared to other maintenance policies.

Chapter 7 investigates joint maintenance and inventory policies, with focus on how the use of predictive maintenance influences inventory decisions. Predictive maintenance is often described as value adding for inventory management due to the better predictability of spare parts demand. However, no hard proof on this statement exists within the available literature. In this chapter we quantify the added value of predictive information in joint maintenance and inventory management by incorporation of an inventory policy into the predictive maintenance model presented in Chapter 6. Chapter 7 addresses RQ3. Moreover, an additional contribution is made by incorporating maintenance and/or spare parts quality into the joint maintenance and inventory decision problem.

Chapter 8 states the major conclusions and research contributions of this dissertation to the present theory and practice. Furthermore, future research directions are discussed.

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Chapter 2

Literature review: maintenance optimization models and criteria

The purpose of this chapter is to provide an overview on maintenance optimization models. It is not the aim to give an exhaustive overview on all published articles, but rather highlight the significance of different maintenance optimization parameters that are of any importance within the frame of addressing the research questions (Section 1.6) of this dissertation. The most important factors that have an influence on the optimization model will be made explicit and their links will be established. This is performed by defining the following parameters that should be taken into account: general modeling techniques; maintenance concepts, policies and actions; maintenance optimization criteria; maintenance effectiveness; deterioration modeling; system information and configuration; data sources; optimization algorithms and output. These classes are discussed into more detail throughout this chapter. Finally, a generic classification framework of maintenance optimization models is presented that will be used in the following chapters on the development of maintenance optimization models taking into account the most relevant optimization influence factors and criteria for a situation at hand. In this way, the framework is a starting point to develop business specific optimization models.

This chapter is based on A. Van Horenbeek, L. Pintelon, and P. Muchiri (2010). "Maintenance optimization models and criteria". In: *International Journal of Systems Assurance Engineering and Management* 1.3, pp. 189–200

2.1 Introduction on maintenance optimization

Many maintenance optimization models have been published over the years as academics have recognized the importance of maintenance optimization. Maintenance decision models can help companies to determine the value of maintenance. Literature provides quite some decision models to determine optimum maintenance policies. However, these are limited to very specific problems. Dekker (1995b) already came to the conclusion that more application oriented research should be done. Currently, the gap between academic models and application in a business specific context is still the biggest problem encountered in the field of maintenance optimization. In literature, case studies are often only used to demonstrate the applicability of a developed model, rather than finding an optimal solution to a specific problem of interest to a practitioner. Nicolai and Dekker (2007) came to the conclusion that case studies are not well represented in maintenance optimization literature, although maintenance is something that should be done in practice and not in theory. Furthermore, Dekker (1996) describes the aspects of maintenance optimization models which cause the gap between theory and practice. He describes six aspects, whereof the most important ones are: models are difficult to understand, many papers are written for mathematical purposes only, companies are not interested in publications and the models often focus on the wrong type of maintenance. Scarf (1997) and Garg and Deshmukh (2006) also address this problem by noting that too much attention is paid to the development of new optimization models, with little regard to their applicability. They come to the conclusion that a shift from theoretical research to applied research is required. This illustrates that the aspect of usefulness by solving real problems through model fitting is often forgotten. Maintenance practitioners do not know which of the many available maintenance optimization models fit their specific problems. Moreover, they lack the time and experience to develop, themselves, an optimization model that satisfies their business specific needs (Dekker 1996). Another limitation perceived in literature is that most of the models have a limited scope by considering only one optimization criterion (i.e. mostly cost) (H. Wang 2002; Van Horenbeek, Pintelon, and Muchiri 2010) without clear proof that this is the real maintenance objective to be optimized within a specific business context. This also makes multi-objective optimization models an underexplored area of maintenance optimization. Although single-objective optimization is attractive from the modeling point of view, this approach does not capture all important aspects of a real-life situation.

Many surveys on maintenance optimization already appeared in literature (Cho and Parlar 1991; Dekker 1995b; Dekker 1996; Jardine, D. Lin, et al. 2006; McCall 1965; Nakagawa 2005; Pham and H. Wang 1996; Pierskalla and Voelker 1976; Scarf 1997; Sharma et al. 2011; Sherif and M. L. Smith 1981; Valdez-

Flores and Feldman 1989; Van Horenbeek, Pintelon, and Muchiri 2010; H. Wang 2002). Although they give a nice overview of different available optimization models, they do not assist practitioners in deciding which model to use or in developing a model that fits their needs. Except for H. Wang (2002), who gives an overview of the influence factors that should be considered in an optimal maintenance policy. But in our view, not all factors are included. Dekker (1995a) also developed a framework that covers several optimization models in a uniform model. Though some research is already done in this field, business specific maintenance optimization and decision making remains a still underexplored area of research. Certainly when looking to the integration of maintenance optimization models into decision making in industry. When looking at multi-objective maintenance optimization some research has already been done (Bucher and Frangopol 2006; Ilgin and Tunali 2007; Martorell, Sánchez, et al. 2002; Tian, D. Lin, et al. 2012; Y. Wang and Pham 2011). But this is still limited to optimizing certain criteria (cost, availability, reliability) while these are not valid or important in certain industrial cases or do not take into account all business specific objectives. One of the concluding remarks Scarf (1997) makes is that the understanding of the optimization process is at least as important as the models themselves. Dekker (1996) supports this view by mentioning that it is important to know which models to use for certain problems. Moreover, a general problem structure that fits most of the problems is necessary.

Based on the above stated problem environment, the objective of this chapter is to develop a general classification framework or problem structure of maintenance optimization models, with special focus on the optimization criteria and objectives. The framework involves listing all factors (e.g. maintenance actions, optimization criteria, maintenance effectiveness) that have an influence on how a maintenance optimization model or methodology is built, and establishing their links. By doing so, knowledge will be gained on how to build an optimization model and on the important factors in certain business specific cases. By doing so, it will be possible to fit already existing optimization models to specific cases if applicable. And if not, the framework will give insight on how to model this optimization process, which is according to Scarf (1997) the most important. Furthermore, the classification framework can be used as a starting point for the development of a new business specific maintenance optimization model, and it is in this way that it will be applied in the following chapters of this dissertation. Hence, the framework will ensure an integration of maintenance optimization models in decision making in industrial settings, and close the gap between academic research and application in practice.

2.2 Maintenance optimization models overview

A literature review on different maintenance optimization models and the input parameters influencing and steering this optimization process is performed. These, together with our own additions, are used to construct the optimization classification framework. The review is structured by defining different important maintenance optimization classes. These optimization classes are groups of input parameters necessary to construct a maintenance optimization model (i.e. general modeling techniques; maintenance concepts, policies and actions; maintenance optimization criteria; maintenance effectiveness; deterioration modeling; system information and configuration; data sources; optimization algorithms). All these maintenance optimization classes will be discussed in the following subsections. Besides these, the possible outputs of a maintenance optimization model will be listed in the last subsection.

2.2.1 General modeling techniques

By general modeling techniques, we mean choices that have to be made for optimization problems in general. The most important ones are: continuous or discrete optimization, static or dynamic optimization, deterministic or probabilistic optimization, constrained or unconstrained optimization and single-objective or multi-objective optimization (Pintelon and Van Puyvelde 2006). Maintenance specific modeling decisions are: component or system perspective and finite or infinite planning horizon. While in most of the optimization models a component perspective is taken, a framework for a predictive maintenance-based schedule derived from a system-perspective is developed by Ming Tan and Raghavan (2008). H. Wang (2002) and Nicolai and Dekker (2007) also take the planning horizon into consideration when classifying different optimization methods. Some maintenance optimization models for finite time periods exist, but these models are still an underexplored area of maintenance optimization (Nicolai and Dekker 2007). Recently, optimization models with a rolling horizon receive more attention as they optimize repeatedly the maintenance schedule on a finite horizon at each decision time. In this way, the long-term maintenance plan can be adapted by incorporating available short-term information (e.g. remaining useful life (RUL)) (Bouvard et al. 2011; Dekker, Wildeman, and van Egmond 1996; Do Van et al. 2011; Van Horenbeek and Pintelon 2013b).

2.2.2 Maintenance concepts, policies and actions

A maintenance concept is a set of maintenance actions and policies and the general decision support structure in which these are planned and supported (Pintelon and Van Puyvelde 2006). Well known maintenance concepts are total productive maintenance (TPM) (Nakajima 1988) and reliability centered maintenance (RCM) (Moubray 1997). The maintenance policies (e.g. failure-based maintenance, time/use-based maintenance, condition-based maintenance and predictive maintenance) trigger a maintenance action when a certain event happens (e.g. failure, time-limit and condition-limit). Different maintenance actions like corrective maintenance, corrective replacement, preventive maintenance and preventive replacement are possible in different situations. The implementations of these concepts, policies and actions all have an influence on the optimization modeling. The focus in this dissertation is on maintenance policies and actions, in the sense of maintenance policy performance comparison and optimization, with special attention given to predictive maintenance policies, by planning the right maintenance actions at their optimal time. All maintenance optimization models, starting from a certain maintenance policy, try to optimize this specific policy. The output of the optimization model will depend on the maintenance policy and actions used. For example, a time-based maintenance policy will optimize the timing of maintenance, while a condition-based maintenance policy also tries to optimize the time of inspection or the maintenance triggering threshold (Jardine and Tsang 2006). Nowadays, maintenance optimization modeling is shifting to optimization of condition-based and predictive maintenance policies (Barata et al. 2002; Camci 2009; Grall, Bérenguer, et al. 2002; Grall, Dieulle, et al. 2002; Jardine, D. Lin, et al. 2006; Marseguerra, Zio, and Podofillini 2002; Tian and Liao 2011; Van Horenbeek and Pintelon 2013b; van der Weide et al. 2010; Yang et al. 2008). In most maintenance optimization models, maintenance action duration (repair and maintenance times) is assumed to be negligible (Pham and H. Wang 1996). However, making this assumption can have a big influence on the determination of the optimal maintenance policy. By making this assumption, availability of the equipment and the value of maintenance are not taken into account. This can result in suboptimal solutions to the maintenance optimization problem, which makes maintenance action duration possibly an important factor to take into account in the maintenance optimization process. Several optimization models already recognize and incorporate this (Boschian et al. 2009).

2.2.3 Maintenance optimization objectives

Optimization is always performed by minimizing or maximizing an objective function. In most of the maintenance optimization models the objective function only takes into account one criterion (e.g. cost, availability, reliability) (H. Wang 2002). Therefore, single-objective optimization is a well studied field in maintenance literature, however, it also limits the scope of the developed models. Some research has been done in the field of multi-objective maintenance optimization (Bucher and Frangopol 2006; Ilgin and Tunali 2007; Martorell, Sánchez, et al. 2002; Okasha and Frangopol 2009; Tian, D. Lin, et al. 2012), but these always take into account the same optimization criteria. These are cost rate, total cost, availability and reliability. In some optimization models safety (Martorell, Villanueva, et al. 2005; Liu 2005) is also considered as one of the objectives. Although this is a nice starting point, not all possible criteria are included in these models. Moreover, no clear-cut method exists on how to determine which criteria are important or should be optimized in a business specific case. It is remarkable to observe that not a lot of attention is paid to the selection of the right maintenance optimization objectives. Definitely because this is one of the most important input parameters for a maintenance optimization model, because optimizing the wrong maintenance objectives always returns a suboptimal solution. It can be concluded that the maintenance criteria or objectives used in literature for optimization are limited to the well-known criteria like cost and availability. For this reason we establish all maintenance optimization criteria that could be of any importance in maintenance optimization and management. These maintenance objectives are used in Chapter 3 to develop a prioritization method to determine whether these objectives are important or not in business specific cases.

Coetzee (1998) states that: "The objective of the maintenance function is to support the production process with adequate levels of availability, reliability, operability and safety at an acceptable cost." So according to Coetzee (1998) there are five important maintenance optimization criteria. Dekker (1996) from his side categorizes the prime maintenance objectives under four headings: ensuring system function (availability, efficiency and product quality), ensuring system life (asset management), ensuring safety and ensuring human well-being. Capital replacement modeling, deciding when to replace a machine with a new one, is another optimization criterion (Jardine and Tsang 2006; Scarf 1997). Other objectives taken into account in literature are safety (Bucher and Frangopol 2006; Martorell, Sánchez, et al. 2002; Martorell, Villanueva, et al. 2005; Liu 2005), maintenance personnel management (Quan et al. 2007) and spare parts inventory (Van Horenbeek, Buré, et al. 2013). Many important maintenance optimization criteria are mentioned in literature, but not all of them are used in maintenance optimization models. In most of the developed models a cost rate or total cost optimization is done (Van Horenbeek, Pintelon, and Muchiri 2010). However, the major benefits of maintenance improvement are usually noticed at other working areas like production, inventory, quality, etc. and not at maintenance itself as it usually shows a higher cost. Marais and Saleh (2009) and Al-Najjar (2007) take a better approach by optimizing the value of maintenance. Moreover, all optimization models used in case studies try to optimize a limited number of maintenance criteria (e.g. cost rate, availability), without clear prove that these criteria are the most important ones in this specific case. This can lead to suboptimal solutions. Maintenance has to provide the right value to the right optimization objectives, not always the maximum or minimum to only one of the objectives. In this way the solution to the maintenance optimization problem will evolve to a global optimum which maximizes the added-value of maintenance by considering multiple decision criteria. To overcome these problems a generic list of all possible maintenance optimization criteria is developed (Table 2.1), taking into account the criteria found in literature and adding the ones we think are also important and are still missing.

Table 2.1: Generic list of optimization criteria.

Maintenance optimization criteria	
Maintenance costs	Availability
Maintenance quality	Reliability
Personnel management	Maintainability
Inventory of spare parts	Environmental impact
Overall equipment effectiveness	Safety/risk
Number of maintenance interventions	Logistics
Capital replacement decisions	Output quantity
Life-cycle optimization	Output quality

When setting objectives in maintenance optimization, one should start from this generic list of maintenance optimization criteria. Based on the experience and expert knowledge available in a company with respect to a specific case, a prioritization among those criteria should be made (see Chapter 3 for a developed prioritization tool based on the analytic network process (ANP)). Based on this prioritization, the real objectives and their importance are derived and an optimal optimization model and solution, with business specific objectives, to the real maintenance problem can be found.

2.2.4 Maintenance effectiveness

In an optimization model the effectiveness of maintenance actions should be taken into account, because in real-life the maintained components are not always restored to an As Good As New state (AGAN). Maintenance effectiveness is the degree to which the operating conditions of an item are restored after a maintenance action is performed. Pham and H. Wang (1996) give an overview of the different possible degrees of restoration:

- *Perfect repair or perfect maintenance*: the operating condition of the system is restored to an as good as new state, which means that the lifetime distribution, degradation level and failure rate are the same as for a new component.
- *Minimal repair or minimal maintenance*: the failure rate of the system is restored to the one the system had before the maintenance action was performed, which is referred to as an As Bad As Old (ABAO) state.
- *Imperfect repair or imperfect maintenance*: the operating condition of the system is restored to somewhere between as good as new and as bad as old.
- *Worse repair or worse maintenance*: the system failure rate or actual age of the system increases by performing a maintenance action, but the system does not break down.
- *Worst repair or worst maintenance*: the system will certainly fail by performing a maintenance action.

Possible causes for imperfect, worse or worst maintenance are repair of the wrong part, partial repair, etc. The Brown-Proschan model (Brown and Proschan 1983) is one of the best known models to account for imperfect repair. Beyond this model, lots of other methods exists to model imperfect maintenance: (p, q) rule, $(p(t), q(t))$ rule , improvement factor, virtual age method, shock model method, (α, β) rule and multiple (p, q) rule. Where the component is returned to the as good as new state (perfect PM) with probability p and to the as bad as old state (minimal PM) with probability $q = 1 - p$. These methods are classified for various maintenance policies by Pham and H. Wang (1996).

2.2.5 Modeling deterioration

Modeling deterioration and the occurrence of failures of a component or system in time forms an essential part of a maintenance optimization model. The performed maintenance actions will only be efficient and effective if they specifically address the most critical and relevant deterioration and failure mechanisms (Dekker 1996). This data provides the basic information on which all decisions about when to perform maintenance or an inspection are made. This description of the deterioration process and failure behavior should match as close as possible with the real time to failure of the system. This makes that many deterioration models are available in literature.

The easiest way to model failure behavior of components is by failure distributions (e.g. Weibull, exponential, normal) (Pintelon and Van Puyvelde 2006), however, a disadvantage of using lifetime distributions is that it only quantifies whether a component is functioning or not. In order to use lifetime distributions to describe aging of components or systems, the failure rate function is widely used (van Noortwijk 2009). However, failure rates cannot be observed or measured for a particular component as it is only useful for a large population of components within the same operating environment rather than for a single component (Singpurwalla 1995). Furthermore, these statistical reliability distributions depend on failure data, which could be unavailable for systems with a high reliability level (Letot and Dehombreux 2012). It is generally more attractive to base a failure model on the physics of failure of a component or failure mode. These physics of failure models assume that the physical degradation process is known *a priori* (e.g. crack growth law), which leads to an analytic expression of the evolution of the degradation (Letot and Dehombreux 2012). However, most of the time the fundamental knowledge of the failure mechanism is lacking, which makes it impossible to make a well-founded forecast of reliability and degradation (Pintelon and Van Puyvelde 2006). Although, there is a clear need to know the health state of equipment at any time from some indicators or features that may be related to the degradation process or a loss in performance. Therefore, degradation is frequently modeled in terms of a time-dependent stochastic process (van Noortwijk 2009). An overview of time-dependent functions where the average rate of deterioration per unit time is modeled by random quantities is given by Frangopol et al. (2004). However, a disadvantage of these random variable models is that the temporal variability is not taken into account (Pandey et al. 2009), which means that a single inspection thus fixes the future deterioration on beforehand. In order to properly model the temporal variability of deterioration for the purpose of maintenance modeling, other stochastic process models are developed. In this way deterioration is usually assumed to be a Markov process (van Noortwijk 2009). An overview of classes of Markov process which are useful for modeling stochastic deterioration is given by van Noortwijk (2009). Two major classes can be defined, namely; discrete-time Markov processes (i.e. Markov chains) and continuous-time Markov processes with independent increments such as the Brownian motion with drift, the compound Poisson process and the gamma process. Each of these models is particularly suitable to model certain types of deterioration. For example, the compound Poisson process is suitable for modeling damage due to sporadic shocks and the gamma process is suitable for describing gradual damage by continuous use. Some particularly interesting works, considering the different described types of degradation models for maintenance optimization are discussed next.

Linear, exponential and logarithmic deterioration and aging models with time are used by several authors (Bucher and Frangopol 2006; Marseguerra and Zio 2000; Letot and Dehombreux 2012). Another common way to model deterioration of components is by using Markov chains (Grall, Dieulle, et al. 2002; Marseguerra, Zio, and Podofillini 2002). Crespo Marquez and Sánchez Heguedas (2002) use a Markov process for repairable systems and finite time periods. A k-state discrete time Markov deteriorating system with time dependent transition probabilities in combination with directed graphs is presented by Marais and Saleh (2009). Although discrete-time Markov processes are used regularly to model deteriorating components, this approach also has some disadvantages. The analytical resolution is difficult in complex cases (Boschian et al. 2009), the classification of states is arbitrary and the transition probabilities are difficult to estimate and may not be elaborate enough in complex cases (Grall, Dieulle, et al. 2002; Liao et al. 2006). A more realistic approach is to model deterioration by a stochastic continuous state process (Liao et al. 2006), though this has the disadvantage of mathematical complexity when modeling complex systems. Grall, Dieulle, et al. (2002) and Dieulle et al. (2003) model a stochastic continuous state deteriorating system by using a Gamma process. Another well known method to model deterioration of components is the proportional hazard model (PHM). This model was first introduced by Cox (1972) and later on reviewed by D. Kumar and Klefsjö (1994). In maintenance this model is often used to estimate the influence of different covariates on the time to failure of a system or component (Samrout et al. 2009). Due to the emergence of condition-based and predictive maintenance, deterioration models for these maintenance policies are developed. Jardine, Makis, et al. (1998) developed a PHM with Weibull baseline function and time-dependent stochastic covariates for condition-based maintenance. This model takes into account both the age of the component as well as the condition of this component. A semi-Markov decision process is used by D. Chen and Trivedi (2005) to model deterioration of a condition-based maintenance problem. A cumulative stochastic point process is used by van der Weide et al. (2010). Marseguerra, Zio, and Podofillini (2002) use Monte Carlo simulation and genetic algorithms to determine the optimal degradation level beyond which a preventive maintenance intervention should be taken by optimizing profit and availability. A multi-component simulation modeling approach is taken by Barata et al. (2002) to find the optimal degradation threshold for performing preventive maintenance actions. Liao et al. (2006) introduce a condition-based availability limit policy which achieves the maximum availability of a system by optimally scheduling maintenance actions. Other papers not only try to find the optimal degradation threshold, but at the same time optimize the inspection schedule or policy (Grall, Dieulle, et al. 2002). Recently many papers address the problem of predictive maintenance decision making. Predictive maintenance uses current and prognostic information, like the remaining useful lifetime of components, to optimally schedule maintenance actions, while condition-based maintenance only uses current component state information. The benefit of also using information about future degradation over only using currently observed information is illustrated in different publications (Camci 2009; Yang et al. 2008). Wu et al. (2007) developed a predictive model that uses an artificial neural network to estimate the life percentile and failure times of roller bearings. Recently, the gamma process has been used to model degradation and predict remaining useful life in predictive maintenance policies (Bouvard et al. 2011; Van Horenbeek and Pintelon 2013b). Proactive maintenance decisions can be made based on the prognostic information which results in a dynamic maintenance schedule.

2.2.6 System information and configuration

System information can be complete or incomplete; when incomplete some expert judgment will be necessary to determine all essential information about the system. Dekker (1996) states that a maintenance optimization model comprises four aspects whereof the first aspect is a description of the technical system, its function and its importance. This is necessary to understand the working principle, determine the criticality, system configuration, etc. of the equipment at hand. Dekker (1996) states that analyzing data without knowing the underlying mechanisms can lead to wrong decisions, which stresses the importance of having the proper system information. Furthermore, this system information will reveal dependence or interactions, when present, between components of a multi-component system. When no dependence between components is present the maintenance decision reduces to an optimal policy for each single component. There are three types of dependence between components, namely economic, structural and stochastic dependence. Nicolai and Dekker (2007) give an overview of maintenance models for multi-component systems using a classification scheme based on the dependence between components. Group maintenance policies and opportunistic maintenance policies are summarized by H. Wang (2002). The problem of component dependence in multi-component systems is specifically addressed in Chapters 6 and 7 of this dissertation.

The system configuration is, together with the component dependence, important system information necessary for maintenance optimization modeling. Different configurations are possible: single-unit, multi-unit, series, parallel, K-out-of-

N, standby, etc. For all of these system configurations different optimization models are available. The review papers all address single-unit and multi-unit systems, while Nicolai and Dekker (2007) review literature on K-out-of-N systems. A maintenance policy for a K-out-of-N system under a condition based maintenance strategy is presented by de Smidt-Destombes et al. (2004) and by Lu and J. Jiang (2007). Pham (2010) estimates reliability of K-out-of-N systems with exponential lifetimes for n independent and identically distributed components. Furthermore, series-parallel systems (Barata et al. 2002; Bris et al. 2003; Coit and A. Smith 1996; Levitin and Lisnianski 1999; Marseguerra, Zio, and Podofillini 2002) and standby units (Vaurio 1997) are also common system configurations addressed in literature.

2.2.7 Data sources

Data availability is often seen as the biggest obstacle to overcome to make the implementation of maintenance optimization models possible in real-life case studies (Dekker 1996). As stated by Caldeira Duarte et al. (2013), there is a clear need for the existence of a maintenance database that provides reliable information for maintenance analysis. Failure data are necessary to model the deterioration of components, operating data to model the working conditions and cost data to evaluate different maintenance policies. The data collected for condition monitoring and predictive maintenance purposes can be categorized into two main types: the so-called event data and condition monitoring data (Jardine, D. Lin, et al. 2006). Event data include the information on when and what happened and/or what was done, while condition monitoring data are the measurements directly related to the condition of the physical asset (Jardine, D. Lin, et al. 2006). However, maintenance information systems mainly contain accounting information on events, while these data are not valuable for maintenance optimization modeling (Dekker 1995b). Moreover, problems exist with the acquisition of cost data. Direct maintenance costs (e.g. personnel cost, component cost) are relatively easy to quantify. However, indirect maintenance costs (e.g. accelerated wear, rework) and the value of maintenance (e.g. increase in availability) are very difficult to determine. Because of these problems some publications were made taking into account model and data uncertainty (Bunea and Bedford 2002; Rocco et al. 2000; Sanchez et al. 2009). A general classification framework of maintenance optimization models, like presented in this chapter, can assist in determining the important data that are necessary in specific cases, reduce uncertainty about some parameters and avoid time loss by gathering irrelevant data. The concept of e-maintenance has the potential to solve the data problem (Muller et al. 2008) by the introduction of IT applications in maintenance (Holmberg et al. 2010). E-maintenance has the capability to provide the decision maker with the right information (e.g. equipment health) at the right time to make the right decision. Moreover the classification framework on maintenance optimization models guides which data should be collected. However, one of the problems e-maintenance is still facing is making the right decision based on all the gathered data, which means the decision models that make the right decision based on the gathered data are still missing (Muller et al. 2008). Liyanage et al. (2009) mentions the development of advanced maintenance simulation software and optimization techniques as one of the most important challenges of e-maintenance applications. An initial idea on how disparate data sources (ie CMMS and CM), commonly available in industry, can be integrated to perform maintenance prognosis and optimal maintenance decision making is discussed by Galar et al. (2012).

2.2.8 Optimization algorithms

When the objectives are set and all necessary information is available an optimization algorithm is used to find the optimal solution to the optimization problem. Analytical and numerical optimization solving are the most common used optimization methods in general (Jardine and Tsang 2006). Weise (2009) gives a general overview of global optimization algorithms and Ehrgott and Gandibleux (2000) review different multi-objective combinatorial optimization methods (e.g. tabu search, simulated annealing, neural networks). An overview of metaheuristics used for optimization is presented by Glover and Kochenberger (2003). In maintenance optimization many algorithms (e.g. linear programming, dynamic programming) are used, which all have their advantages on solving specific problems. However, in most of the real-life maintenance optimization cases, more advanced models and optimization algorithms are required to ensure a good fit between the model and the industrial problem. In the last few years academics have recognized this, which makes a combination of simulation (e.g. Monte Carlo simulation) and heuristic algorithms for optimization (e.g. evolutionary algorithms) (Coello 2000; Marseguerra, Zio, and Podofillini 2002; Villanueva et al. 2008) a promising combination to be used in complex maintenance optimization problems (Van Horenbeek, Pintelon, and Muchiri 2010). Optimization algorithms used in maintenance optimization applications are listed in the classification framework described in Section 2.3 of this chapter.

2.2.9 Output

Dekker (1995b) describes the results or output of a maintenance optimization model. First, maintenance policies can be evaluated and compared with respect to the optimization objectives and criteria. Only cost and reliability characteristics are mentioned as criteria by Dekker. Secondly, models can determine how often and when to inspect or maintain. In other words, they assist in taking a timing decision. And finally, optimization models can help to determine effective and efficient maintenance schedules and plans (e.g. execution moments, planning shutdowns, work preparation, required maintenance capacity). Jardine and Tsang (2006) introduce a framework consisting of four key decision areas for optimizing equipment maintenance and replacement decisions. Each of these four areas returns specific outputs; these are (i) component replacement time, (ii) inspection time and frequency, (iii) capital equipment replacement (e.g. economic life, repair vs. replace) and (iv) resource requirements (e.g. workshop machines, crew sizes and composition, lease or buy, outsourcing).

2.3 Classification framework of maintenance optimization models

Based on the maintenance classes discussed in Section 2.2 it is possible to define a general classification framework of maintenance optimization models. Maintenance optimization models are already categorized by several authors (Brown and Proschan 1983; Cho and Parlar 1991; Nicolai and Dekker 2007; Pham and H. Wang 1996; H. Wang 2002), but there is always a limited focus on certain subjects (e.g. imperfect maintenance and component dependence) of maintenance and a general overview of maintenance optimization models was never given. By defining a general classification framework it is possible to determine which factors should be taken into account in the maintenance modeling process. Moreover, the framework is used as a starting point for the maintenance models developed within this dissertation. In this way this approach also initiates the closing of the gap between academic research and practical application of maintenance optimization models.

2.3.1 Maintenance optimization classification framework

Dekker (1995b) states how he sees an optimization model. It is a description of a technical system, its function and its importance, deterioration of the system, available system information, an objective function and an optimization technique. H. Wang (2002) developed a general framework for maintenance policy optimization. The inputs used for this framework are: maintenance policies, system configuration, maintenance effectiveness, maintenance cost, optimization criteria, modeling tools, planning horizon, dependence and system information. By changing the system configuration, maintenance effectiveness, planning horizon, analytical tools and dependencies between components, different optimization models are obtained according to Marais and Saleh (2009). Although this gives a good idea about how a maintenance optimization model is built, not all optimization classes discussed in the literature study of Section 2.2 are present. Taking these optimization classes into account, together with the optimization criteria, a general maintenance optimization classification framework is built (Figure 2.1). This framework gives an overview of all possibilities for maintenance optimization modeling. The optimization classes (Section 2.2) are the input parameters necessary to construct a maintenance optimization model, and this model will generate the wanted output.

2.3.2 Application of the classification framework

Dekker (1996) states the need for a set of standard maintenance models that fit different optimization problems. This can be difficult to achieve in reality, but a methodology on how to reach an optimization model that fits a business specific case can be developed. The developed maintenance optimization classification framework gives an overview of all variations that can be considered for maintenance optimization modeling. This makes it easier for industrial companies, as well as for academics, to see what is possible with the current maintenance optimization techniques and which areas still need some further research. The general framework of optimization models presented in this chapter can be a starting point to fit a maintenance optimization model to a specific problem. In this way a business specific model can be built, starting from the general classification framework and determining the important business specific input parameters for the model. Moreover, the framework not only assists in developing a maintenance optimization model, it also helps practitioners to find existing maintenance optimization models that fit their specific needs. Another problem addressed by the classification framework is the data problem mentioned earlier in this chapter. The maintenance optimization classification framework helps to determine which data are important to incorporate in the optimization model in specific cases. The presented classification framework is an initial step to develop the maintenance models presented in the following chapters of this dissertation.

2.4 Conclusions

The presented literature review on maintenance optimization models shows that already a lot of research has been done in this field. However, many possibilities

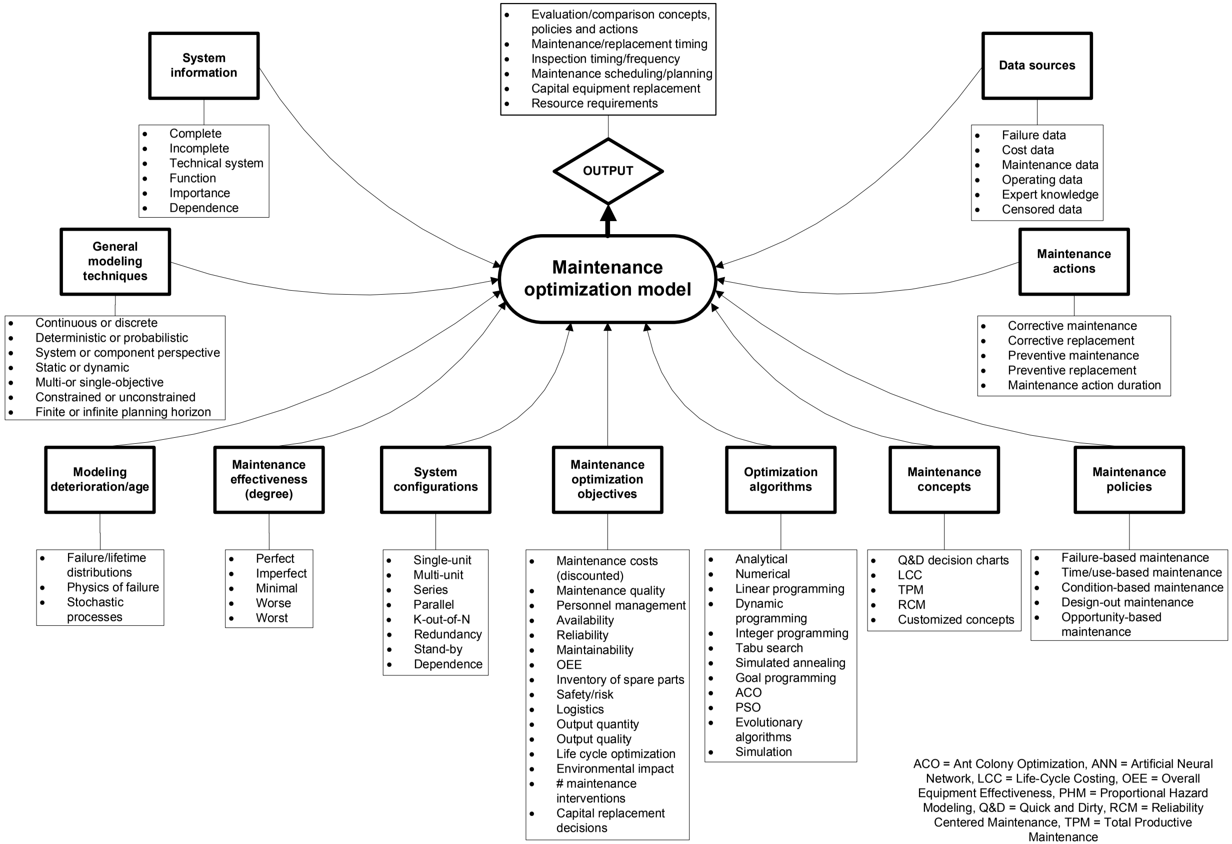

Figure 2.1: Maintenance optimization classification framework.

to extend the existing models can be derived. The most important ones, as already stated in Chapter 1, can be summarized as follows: (i) development of predictive maintenance decision support tools and models, (ii) literature urges for a need for more application based maintenance optimization, (iii) the limited scope with regard to maintenance objectives and criteria and (iv) availability of maintenance data.

The presented general classification framework of maintenance optimization models is used to address these issues in the following chapters of this dissertation. The framework describes and links all possible maintenance optimization techniques and parameters. A clear overview of all important parameters that need to be considered when developing new maintenance models is given. By doing so, the framework is used in the following chapters to construct an information-based maintenance methodology by developing business specific maintenance optimization models. The target is to construct a decision support structure on how to implement a maintenance optimization model and methodology for a given industrial environment considering the available maintenance data.

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Chapter 3

Development of a maintenance performance measurement framework: using the analytic network process (ANP) for performance indicator selection

The objective of this chapter is to answer the first research question, defined in Section 1.6.1, by developing a model to determine and prioritize business specific maintenance objectives that can be used for maintenance optimization. Hence, an analytic network process (ANP) model for maintenance objective selection is presented. However, by doing so, it became clear that the developed model has a wider applicability within maintenance performance measurement, rather than only selection of business specific maintenance objectives. Therefore, the scope of this chapter is broader than initially planned, and discusses the

This chapter is based on A. Van Horenbeek and L. Pintelon (2014). "Development of a maintenance performance measurement framework - using the analytic network process (ANP) for maintenance performance indicator selection". In: *Omega* 42, pp. 33–46 development of a maintenance performance measurement (MPM) framework, wherein part of the methodology specifically addresses the first research question of this thesis, which is defined as follows:

> *"How to determine and prioritize business specific maintenance objectives which can be used for maintenance performance measurement (MPM), management and optimization?"*

In order to ensure a good performance of the production plant, maintenance managers need a good overview of maintenance processes and achievements. This can be attained by a rigorously defined maintenance performance measurement system and maintenance performance indicators (MPI). Many performance measurement frameworks and indicators are presented in literature; however some major issues remain unresolved. Many papers discuss the development of generic maintenance performance frameworks and corresponding indicators; however none of the publications considers the selection of relevant MPI for a specific business context and consequently in relation with the company's maintenance objectives. Moreover, the link with the manufacturing and corporate strategy should be established in order to establish an MPM system usable throughout the entire company. In this way, maintenance performance measurement should be defined on all management levels (i.e. strategic, tactical and operational). To overcome these problems, the objective of this chapter is to develop an MPM framework that aligns the maintenance objectives on all management levels with the relevant MPI used. In order to assist the maintenance manager on selection of the relevant MPI, an analytic network process (ANP) model and methodology is presented which is based on the designed MPM framework. The methodology is applied to several case studies considering companies from different types of industry. The results illustrate the applicability and capability of the presented MPM framework and ANP model to assist maintenance managers in the definition and selection of MPI in line with the maintenance and corporate objectives and strategy. The ANP approach enables the decision maker to better understand the complex relationships in the decision problem, which improves the reliability of the corresponding decisions.

3.1 Problem delineation

Within maintenance management, maintenance performance measurement (MPM) is perceived as an important function to achieve sustainable performance of any manufacturing plant (Muchiri, Pintelon, Gelders, et al. 2011; Pintelon and Van Wassenhove 1990). In order to achieve this, maintenance managers need a good track of maintenance process performance, which can be achieved by a rigorously defined performance measurement system (MPM) and indicators

(MPI) that are able to measure maintenance function performance. This is reflected and supported by the many proposed MPM approaches in literature. Recently, extensive literature reviews on the implementation of performance measurement systems (Bourne et al. 2003) and maintenance performance measurement (Simões et al. 2011) have been published. Despite the extensive research on maintenance management and performance measurement, still some major flaws in the available methodologies remain unsolved. The link between the strategic objectives of the company and the corresponding MPI is lacking. Together with the lack of a methodological approach to select business specific MPI based on the corporate strategy and derived maintenance objectives, these form the major directions of future research necessary to improve currently available MPM systems.

MPM systems need to be aligned with the corporate or organizational strategy (Kaplan and Norton 2001; Murthy, Atrnes, et al. 2002; Grigoroudis et al. 2012). In order to accomplish the top-level objectives of the maintenance strategy, these objectives need to be translated to the lower levels of the organizational structure (Parida and U. Kumar 2006). Crespo Marquez and Gupta (2006) propose to align maintenance management with all actions at the three levels of business activities (i.e. strategic, tactical and operational). Maintenance priorities in order to derive and track maintenance performance must be set according to criticality functions directly linked to the company's business goals. The authors mention that a main concern for business management is establishing the parameters influencing the criticality function and their relative weight, which changes according to the current business environment. Moreover, there is little literature available on the development of a systematic approach that embraces every level of business activities (i.e. strategic, tactical and operational) (Kutucuoglu et al. 2001). Parida and Chattopadhyay (2007) presented a multi-criteria hierarchical maintenance performance measurement framework to resolve this issue, however their framework does not provide any guidance on the selection of business specific MPI. This brings us to the second major flaw in MPM systems identified from literature.

The available literature mainly proposes common lists of MPI but lacks an agreed-upon methodological approach of selecting or deriving business specific MPI from the listed indicators in literature (Muchiri, Pintelon, Gelders, et al. 2011; Muchiri, Pintelon, Martin, et al. 2009). Therefore, maintenance managers are left to select relevant MPI for their specific business situation. As it is definitely not feasible to monitor or measure all of the available indicators due to the increase in number and type of measures (U. Kumar 2006), selection of MPI in line with the business environment and maintenance strategy is crucial. Swanson (2001) identifies the formulation and selection of MPI that reflect a company's organizational strategy as a major issue. Moreover, Muchiri, Pintelon, Gelders, et al. (2011) mention that an operational level based maintenance measurement model that links maintenance objectives to maintenance processes and results is lacking. The development of such a model could provide a basis to identify business specific MPI for the maintenance function. The study performed by Muchiri, Pintelon, Martin, et al. (2009) revealed a lack of direct alignment between the maintenance objectives and the maintenance MPI used, while one would expect that the MPI used in a company are directly influenced by the maintenance objectives and in accordance with the needs of its manufacturing environment. Moreover, only a minority of the companies have a high percentage of decisions triggered by the defined MPI. These results definitely raise doubts on the effectiveness and efficiency of currently defined and implemented MPM systems. Among the issues proposed in future research is the establishment of a methodological approach of deriving MPI from maintenance objectives. Such an approach can potentially support maintenance managers in deriving business specific MPI. Performance measurement, when used properly, should highlight opportunities for improvement, detect problems and derive corresponding solutions (Wireman 2005); which is currently not the case according to the study of Muchiri, Pintelon, Martin, et al. (2009).

As a conclusion, it can be summarized that most models, methodologies and frameworks on MPM are generic, without considering the business specific environment of the company where these tools should be applied. Therefore, the link between the corporate strategy and the used MPM and corresponding MPI is not established in a proper way. A second major flaw in the available literature on MPM is the lack of methodological approach to select or derive business specific MPI. The objective of this chapter is to tackle these issues by proposing a new MPM framework which is based on the corporate and maintenance strategy, by incorporating all organizational levels (i.e. strategic, tactical and operational). Furthermore, an ANP model to determine business specific maintenance objectives and corresponding MPI based on the developed MPM framework is presented. This directly addresses the first research question as defined in Section 1.6.1. The link between corporate strategy, maintenance objectives, MPI, decision making and continuous improvement is concretized. In this way, a customized MPM with corresponding MPI that fits the business specific environment and needs of a company is derived. The methodology assists decision makers and more specifically maintenance managers in the selection of MPI in line with their specific maintenance and manufacturing strategy. The developed methodology is applied to five industrial case studies to illustrate and validate the proposed approach. An overview and short description of the case studies is given as follows:

- Company A: manufacturer of wind turbine components

- Company B: manufacturer of industrial systems and provider of additional service contract
- Company C: medium size hospital
- Company D: large university hospital
- Company E: military aircraft operator

The remainder of this chapter is organized as follows. Section 3.2 of this chapter describes the developed maintenance performance measurement (MPM) framework and applied methodology in detail. An overview of the ANP methodology applied to one specific case study is given in Section 3.3. Section 3.4 discusses the selection of business specific MPI. Finally, a discussion and managerial implications are given in Section 3.5 and Section 3.6 states the major conclusions.

3.2 Maintenance performance measurement (MPM) framework

This section presents in detail the developed maintenance performance measurement (MPM) framework. Furthermore, based on the literature review of Chapter 2, an overview of the maintenance objectives and criteria considered on the different organizational levels (i.e. strategic, tactical and operational) is given.

3.2.1 General framework and methodology

Availability of maintenance performance frameworks and indicators may not necessarily guarantee performance improvement (Muchiri, Pintelon, Gelders, et al. 2011). The main reason for this is that the developed maintenance performance frameworks in literature are too generic, as MPM frameworks can be seen in most cases as a list of maintenance objectives and MPI. Consequently, as stated in the introduction, they do not provide any guidance on the selection of relevant maintenance objectives (Section 1.4) and corresponding MPI for a specific business environment (Section 3.1). The objective of the proposed MPM framework (Figure 3.1) is to link the generically defined MPM frameworks with the business environment and corporate strategy of an organization and in this way develop a customized MPM system. The proposed methodology and steps that need to be followed to achieve this are shown in the framework of Figure 3.1. As can be seen the proposed ANP model, discussed into more

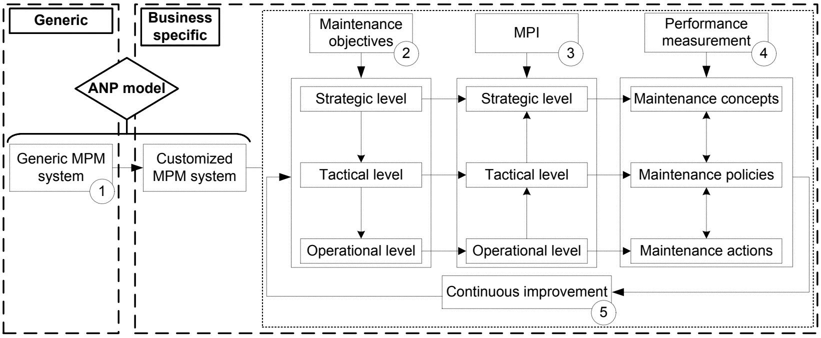

Figure 3.1: Maintenance performance measurement (MPM) framework which horizontally reflects the MPM process and vertically incorporates all organizational levels of decision making.

detail in the next sections of this chapter, is the enabler to define and develop a customized business specific MPM system. This is performed by defining and prioritizing maintenance objectives on all organizational levels in a first phase, herewith addressing the first research question (Section 1.6.1), and deriving the corresponding MPI in a second phase. In this way, the selection of MPI is based on a prioritization of business specific maintenance objectives. The ANP model allows to analyze maintenance objectives tailored to each organizational level which emanate from the corporate level. The maintenance objectives and strategy are derived from the corporate goals and objectives based on the stakeholders' expectations, while ensuring that these objectives are correctly translated into subgoals at lower organizational levels. Crespo Marquez and Gupta (2006) suggest that actions at the strategic level will transform business priorities into maintenance priorities, actions at the tactical level determine the correct assignment of maintenance resources to perform maintenance and actions at the operational level ensure the proper execution of maintenance tasks. The strategic goals need to be broken down into objective targets on the operational level. This makes the definition of maintenance objectives a top-down approach (Figure 3.1) by translating objectives on higher organizational levels to subgoals at lower organizational levels. The next step is to translate the derived maintenance objectives into relevant MPI on each organizational level, as the defined metrics should serve specific levels of the organizational hierarchy. This in order to solve the lack of direct alignment between the maintenance objectives and the used MPI as defined in the study of Muchiri, Pintelon, Martin, et al. (2009). This approach leads to the definition of multi level indicators. By defining MPI based on the multi level maintenance objectives of the company it can be assured that the MPI reflect the maintenance objectives and corporate strategy. The determination of business specific MPI is opposed to the definition of maintenance objectives a bottom-up approach (Figure 3.1) through the organizational levels, as the higher level metrics are a product or aggregation of several lower level indicators. Consequently, the subjectivity increases as the management level becomes higher due to the fact that objective outputs at lower levels are integrated in MPI at higher strategic levels. Based on the defined MPI, the performance of the applied maintenance concepts, policies and actions (Pintelon and Van Puyvelde 2006) can be measured, monitored, controlled and optimized. As a final step maintenance decision making and optimization, by continuous improvement, should be performed in order to achieve maximal performance on the defined business specific MPI and achieve the maintenance objectives by closing the gap between actual performance and potential performance.

Hence, the proposed methodology to develop a business specific MPM system based on the defined framework of Figure 3.1 consists of five major steps that can be summarized as follows:

1. Translate a generic MPM system to a customized MPM system considering all organizational levels (i.e. strategic, tactical and operational).
2. Prioritize maintenance objectives on all organizational levels (top-down approach) to derive business specific maintenance objectives based on the developed ANP methodology and model (i.e. first research question (Section 1.6.1)).
3. Translate the business specific maintenance objectives into relevant MPI on each organizational level (bottom-up approach).
4. Measure, monitor, control and optimize maintenance performance based on defined MPI.
5. Continuous improvement by redefining maintenance targets according to the business environment.

In this chapter we focus on the first three steps of the proposed methodology, as within the currently available research on MPM systems these are identified as the ones with major potential for improvement. The last two steps are subject of further study in the following chapters of this dissertation.

3.2.2 Literature overview of maintenance criteria and objectives

In order to define a generic MPM framework, which is the first step in the proposed methodology, it is of utmost importance to define all relevant maintenance criteria and objectives that possibly could be of any importance in the decision process. A literature review on maintenance criteria and objectives is performed in Section 2.2.3 to achieve this. Based on this literature and the experience of the authors a generic list of maintenance objectives on the strategic and tactical levels of the organization can be summarized as follows:

- maintenance budget (MB): maintenance costs (MC), maintenance value (MV)
- functional and technical aspects (F&T): availability (A), reliability (R), maintainability (M), Overall Equipment Effectiveness (OEE), productivity (P), output quality (OQ) and maintenance quality (MQ)
- plant design life (PDL): capital replacement decisions (CRD) and life-cycle optimization (LCO)
- support (S): inventory of spare parts (I) and logistics (L)
- people and environment (P&E): environmental impact (EI), safety/risk/health (SRH) and personnel management (PM)

Further subdivision of maintenance objectives into the operational level of an organization is possible according to the objectives defined in Figure 3.2. Note here, the complexity of the decision problem increases with an increase in the number of maintenance criteria. Based on the defined generic maintenance objectives it is possible to develop a generic MPM framework (see Section 3.3.2), similar to the ones available in the currently available literature (Bourne et al. 2003). However, the derived maintenance objectives should be prioritized according to the business specific environment and linked to corresponding MPI as illustrated in Figure 3.1 and discussed in Section 3.2.1 in order to overcome the identified shortcomings in the current MPM systems. This prioritization and derivation of business specific maintenance objectives and corresponding MPI is performed by the application of the developed ANP methodology (Section 3.3).

3.3 Analytic Network Process (ANP) methodology

This section discusses the reasons to adopt an ANP methodology to select business specific maintenance objectives and corresponding MPI. Furthermore, an overview of the applied ANP methodology and its different steps is discussed. However, the interested reader is referred to the work of Saaty (Saaty 1996; Saaty and Ozdemir 2005) for more detailed information, as the objective of this section is not to describe the ANP methodology in detail, but to apply it to the formulated research problem. Five industrial case studies have been performed in order to illustrate and validate the developed MPM framework and ANP

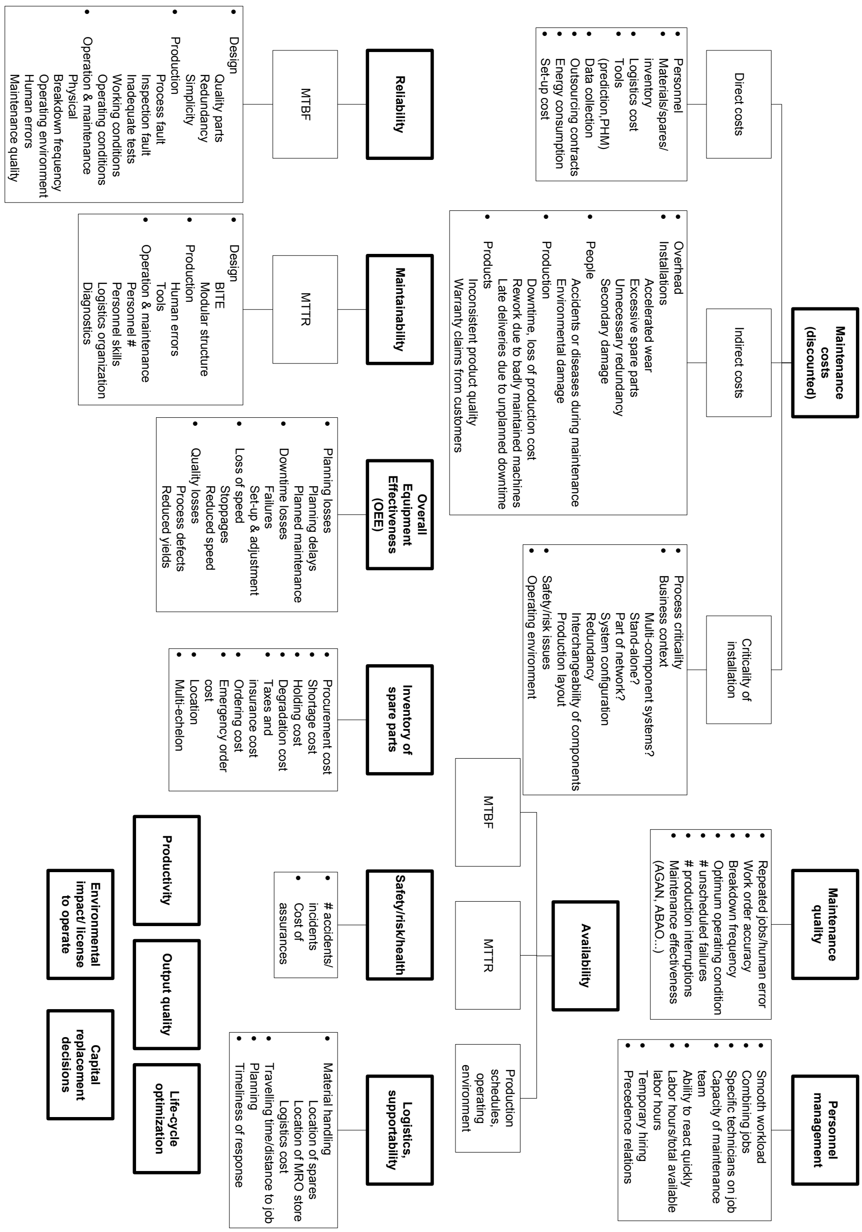

Figure 3.2: Tactical maintenance objectives further subdivided into operational maintenance objectives.

model. As an illustrative example and for the reason of brevity only the case study performed for company D is discussed into detail by considering the five major steps of the ANP methodology in Section 3.3.2. For the remaining case studies only the results are shown. The applied ANP methodology and its different steps are however applied in the same way as discussed for company D for all case studies.

3.3.1 Prioritization and selection methodology

The literature points to the existence of trade-offs among different aspects of performance (Da Silveira and Slack 2001). Performance measures tend to be traded-off against each other as they are not equally important (Slack and Lewis 2008). In order to make this trade off possible, a prioritization and selection methodology for the maintenance objectives defined in Section 3.2.2 should be developed. Striving towards optimal maintenance should be done by setting the right and business environment specific maintenance objectives. Does a company strive towards lowest cost, maximal availability of equipment or maximal safety of the maintenance personnel? These objectives determine the strategy of a maintenance department. Moreover, a distinction should be made between objectives on the highest organizational levels and lower organizational levels (Section 3.2.1). For example, tactical level objectives are used for maintenance policy selection and optimization, while operational level objectives are used to plan maintenance activities. The objectives on the highest levels should be translated to relevant objectives on the lower organizational levels.

To make a decision about which maintenance objectives are important a comparison process is necessary. This comparison process is used to evaluate the different criteria and make a decision about which maintenance objectives are important to achieve the corporate business strategy and optimal performance. This evaluation and decision making is in real life based on the expert knowledge and judgment of the decision makers. In order to establish the link between the proposed generic MPM frameworks in literature, the maintenance objectives defined in Section 3.2.2 and a business specific maintenance performance system, an ANP model is adopted in this chapter (Figure 3.1). ANP is an extension of the analytic hierarchy process (AHP), where the assumption of independent criteria is not valid (Saaty 1996). In this chapter ANP is used to prioritize between the different maintenance objectives because several maintenance related objectives are interlinked and interdependent, like for example availability and reliability (Muchiri, Pintelon, Martin, et al. 2009). Applying this method (i.e. ANP) to the selection of business specific maintenance objectives is a starting point to a customized MPM framework as discussed in Section 3.2.1.

There are different reasons why the ANP methodology is believed to be the most suitable to select the most important maintenance objectives for a business specific environment. First of all, ANP is a proven strategic decision support method which is used in many applications (Saaty and Ozdemir 2005; Jharkharia and Shankar 2007; Partovi 2006; Verdecho et al. 2012). Based on expert knowledge of the decision maker, both quantifiable and non-quantifiable parameters can be incorporated into the methodology. This is essential because in some cases criteria are difficult to express quantitatively, such as safety. The difficulty to express preference between different criteria in the decision problem is countered by allowing minor inconsistency in the pairwise comparisons. Nevertheless, this should be limited to achieve a good solution. Therefore, the consistency of the decision maker is checked by calculating a consistency ratio. Moreover, interdependence between criteria is taken into account (e.g. availability and reliability), so ANP is a useful tool in an environment with many opposing influences, such as the different targets of a production and maintenance department, for which a balance should be found. In addition, the ANP scale of measurement is ratio based. This measurement describes the scale on which the resulting priorities are based. In order of increasing strength these are: nominal, ordinal, interval and ratio scales (Stevens 1946). The more powerful the scale, the better the assessment of the final priorities. Furthermore, ANP uses pairwise comparisons to derive priorities amongst the considered criteria in the decision process. In this way, decision makers gain knowledge and insight into the problem when performing the process of comparison between the different criteria. This makes direct involvement of decision makers in the process of selecting relevant maintenance objectives an important requirement to formulate the right maintenance strategy. Finally, ANP structures the problem into a network structure, in this way different organizational levels can be reflected in the network structure in order to derive maintenance objectives on all organizational levels (Figure 3.1). Based on both the problem structure faced for selection of maintenance objectives and the inherent characteristics of the ANP method, this is found to be the best method to prioritize among the maintenance objectives.

3.3.2 Application of ANP methodology

Step 1. Develop team of competent managers

As the ANP methodology makes use of a comparison process, group decision making may be used to avoid the possible biased attitude of a single decision maker. Dyer and Forman (1992) propose several ways in order to include the views and judgments of group members in the comparison process. These are (i) consensus, (ii) vote or compromise, (iii) geometric mean of the individual's judgments, and (iv) a separate model. For all case studies considered in this chapter a structured analysis and discussion is performed until consensus is achieved between all decision makers involved in the decision process. Consensus is believed to be the best approach as many opposing influences, such as the different targets of a maintenance and production department, need to be balanced by discussion. Aggregation of individual results without any discussion on the decision problem would, opposed to consensus, only lead to an averaged result of all individual results. Preferably, the experts involved in the decision process should be at least one maintenance manager, one manufacturing manager and one general manager. This is necessary to represent different departments and all organizational levels of the respective companies. For the case study performed at company D, the decision making group consisted of one quality manager and one reliability engineer. The reason no manager affiliated to manufacturing is considered in this case study is simply because in a hospital environment nothing is manufactured. For this reason it was believed that a quality manager, with specific knowledge about the general business/organizational objectives and a reliability engineer, with specific expert knowledge about equipment reliability and maintenance processes formed an expert decision group capable of performing the comparison process.

Step 2. ANP network and problem formulation

In the ANP methodology, an extension of the well known analytic hierarchy process (AHP), the decision problem is transformed into a network structure. This network structure is built based on the comprehension of the decision problem and the links between the different factors in the decision problem. It is possible to incorporate different kinds of relationships between the considered factors. The network structure is composed of different clusters (groups of elements) and elements that are connected with each other. These connections represent the different relationships that exist between the clusters and elements in the decision problem. A cluster is connected to another cluster when at least one element in the first cluster is connected to at least two elements in the other cluster. Between the clusters and its elements different relationships (inner dependence, outer dependence, feedback) exist (Figure 3.3). The direction of the arrows in the network structure is important to represent the right relationship between two clusters. The difference, in established relationships and links, between a hierarchy (AHP) and network (ANP) is illustrated in Figure 3.3. A hierarchy is a linear top down structure with no feedback from lower to higher levels and independency of the elements within their own level. Unlike a hierarchy, a network does not have the same linear structure. The clusters are not arranged in a particular order and spread out in different directions. Moreover, the ANP network allows for inner dependence (i.e. elements of a cluster depend on each other) and outer dependence (i.e. feedback between clusters from lower to higher levels). Outer dependence is expressed either from one cluster directly to another one or either by transiting influence through intermediate clusters along a path that sometimes returns to the original cluster, forming a cycle. The different components in a network structure are: source component (no incoming arrows), sink component (no leaving arrows), recurrent state (falls on a cycle) and transient state.

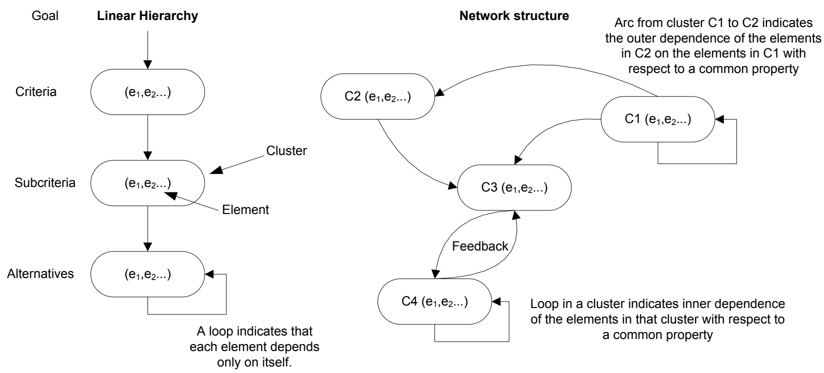

Figure 3.3: Comparison of hierarchy (AHP) and network (ANP) structure.

Based on the literature overview of Chapter 2 and Section 3.2, and informal discussions within the frame of the case studies, a generic network structure (i.e. elements, clusters and relationships) for maintenance objective prioritization and selection is presented in Figure 3.4. Only the strategic and tactical level are considered in Figure 3.4 and further on in this chapter. It is however straightforward to extend the network by including the operational maintenance objectives given in Figure 3.2. In fact this network structure can be seen as a generic MPM system considering an exhaustive list of maintenance criteria and corresponding relationships. As defined in Section 3.2.1, the development of this generic MPM system fits into the first step of the proposed methodology. The goal of the decision problem is to find, based on the generic network structure, the maintenance objectives that are the most important on each organizational level in a certain business environment. In other words, which of these criteria influences the maintenance strategy and operations the most? The single element cluster “goal” is directly connected to the decision problem and it will be used as the control criterion in the ANP methodology. At a second level in the network structure are the strategic maintenance objectives (i.e. maintenance budget, functional and technical aspects, plant design life, support and people and environment). These strategic maintenance objectives are groups of tactical maintenance criteria that are all related to the same strategic objective. So these different strategic maintenance objectives all form a cluster in the network with different elements (i.e. tactical maintenance objectives). All possible interdependencies between the different elements and clusters in the network structure are also shown in Figure 3.4. For example, when availability depends on the reliability and maintainability of equipment; this introduces an inner dependence loop in the functional and technical aspects cluster in the network (i.e. link D in Figure 3.4). All other possible dependencies between elements and clusters are taken into account in the same way and are shown in Figure 3.4 and in the corresponding supermatrix which is given in Table 3.1.

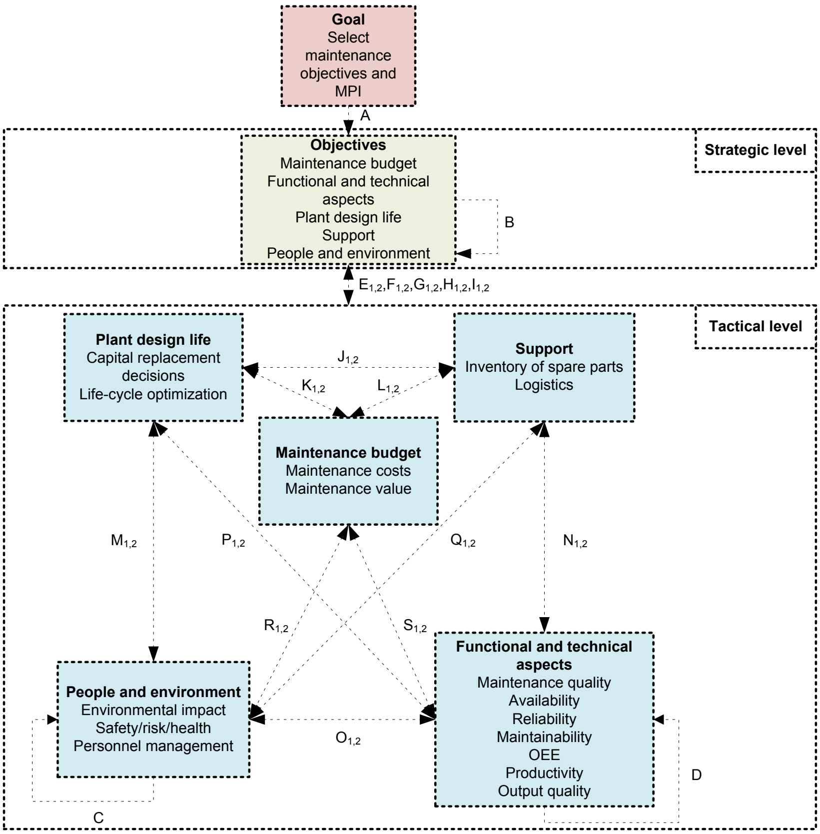

Figure 3.4: Generic ANP network structure for maintenance objective and MPI selection.

The generic network structure of Figure 3.4 is constructed in order to assist the decision makers for the specific case studies. In this way, this first step in the ANP methodology reduces to modifying the proposed network structure according to the business specific environment of an organization. This is done by selecting the relevant elements for the decision problem and defining the relevant relationships between elements and clusters in the network structure. For example, for company D "maintenance value" was dropped as a maintenance objective, as it proved to be very difficult to quantify the value of maintenance throughout the entire hospital. Note that several relationships as defined in Figure 3.4 are omitted for the case study in company D. Further details on this are given in the following sections. Hence, the proposed generic network structure is customizable according to the business specific environment of an organization by adapting the elements, clusters and defined relations in the general decision structure. This finally results in a customized MPM system (i.e. step 1 of the proposed methodology in Section 3.2.1).

Step 3. Pairwise comparisons

After the decision problem is transformed into the right business specific network structure, pairwise comparisons between the different clusters and elements are performed in order to derive overall priorities. The decision maker provides a judgment from the fundamental AHP scale (i.e. a ratio scale of 1-9) developed by Saaty (1990). This judgment reflects the dominance between elements or clusters in the ANP network; it gives an answer to two kinds of questions (Saaty 1996):

1. Given a criterion, which of two elements is more dominant with respect to that criterion?
2. Which of two elements influences a third element more with respect to a criterion?

All influences should be considered with respect to the same criterion to derive the overall priorities, which means that all comparisons should be made with regard to one criterion, the control criterion (i.e. the "goal" criterion in Figure 3.4) of the ANP network. In this way synthesis of the problem is meaningful and overall priority vectors can be derived, not only taking the explicitly known relations into account, but also the relations through feedback in the network. For each relevant relation between clusters and/or elements defined in the network structure a pairwise comparison matrix needs to be constructed. The number of pairwise comparisons that should be performed for an $n \times n$ pairwise comparison matrix equals $n \times (n-1)/2$, where n is the number of elements that needs to be compared. This is the case because the comparisons on the diagonal of the matrix all equal one. Moreover, only the pairwise comparisons at the top right triangle of the matrix should be performed, because the left bottom triangle contains the reciprocal values of these comparisons. The pairwise comparison number a_{ij} is the number of the fundamental scale (Saaty 1990) that approximates the ratio w_i/w_j, where w_i is the weight or priority of the i^{th} element (row element) and w_j is the weight or priority of the j^{th} element (column element). In this way a score of 1 of the defined ratio scale indicates equal importance of the two elements given a control criterion whereas a score of 9 indicates overwhelming dominance of the i^{th} element over the j^{th} element. The final matrix is a positive reciprocal near consistent pairwise comparison matrix. In the formation of the pairwise comparison matrices, group decision making (i.e. consensus (Section 3.3.2)) is used to avoid the possible biased attitude of a single decision maker. For reasons of brevity only a selection of the total number of 35 pairwise comparison matrices, considered in the case study for company D, is given. However, these are chosen in a way that all possible dependencies like discussed in Section 3.3.2 are illustrated. Therefore, the remaining pairwise comparisons, not illustrated here, are performed in the same way. The types of dependence can be defined as follows:

- *Outer dependence with respect to the goal criterion*: the objectives cluster is outer dependent on the goal (i.e. link A in Figure 3.4). The corresponding pairwise comparison matrix is shown in Table 3.2.
- *Inner dependence*: the elements of the functional and technical aspects cluster are inner dependent (i.e. link D in Figure 3.4). The corresponding pairwise comparison matrix is shown in Table 3.3.
- *Outer dependence on different management levels*: the elements in the functional and technical aspects cluster are outer dependent on the functional and technical objective in the objectives cluster (i.e. link F1 in Figure 3.4). The corresponding pairwise comparison matrix is shown in Table 3.4.
- *Outer dependence on the same management level*: the functional and technical aspects cluster elements are outer dependent on the maintenance costs on the tactical management level (i.e. link S1 in Figure 3.4). The corresponding pairwise comparison matrix is shown in Table 3.5.

Step 4. Priority vector calculations and consistency check

After all pairwise comparisons between the criteria and clusters are performed by the decision makers; priorities or weights for all criteria need to be derived from these judgments. Different methods to do this are described in literature (Saaty and G. Hu 1998; Fichtner 1986; Barzilai 1997). As Saaty (1996) states: “With the idea of dominance, the principal eigenvector, known to be unique to within

Table 3.1: Super matrix formation according to the generic ANP network structure of Figure 3.4.

	G	O	MB	F&T	PDL	S	P&E
Goal (G)							
Objectives (O)	A	B	E2	F2	G2	H2	I2
Maintenance budget (MB)		E1		S2	K1	L1	R2
Functional and technical aspects (F&T)		F1	S1	D	P1	N1	O1
Plant design life (PDL)		G1	K2	P2		J2	M2
Support (S)		H1	L2	N2	J1		Q2
People and environment (P&E)		I1	R1	O2	M1	Q1	C

Table 3.2: Pairwise comparisons of objectives with respect to the goal criterion.

Goal	MB	F&T	PDL	S	P&E	Priorities	CR
Maintenance budget (MB)	1	1/7	1/5	1/3	1/7	0,0369	
Functional and technical aspects (F&T)	7	1	1	7	1/2	0,2562	
Plant design life (PDL)	5	1	1	3	1/5	0,1681	0,0696
Support (S)	3	1/7	1/3	1	1/7	0,0629	
People and environment (P&E)	7	2	5	7	1	0,4758	

Table 3.3: Pairwise comparisons of functional and technical aspects with respect to OEE.

OEE	A	P	OQ	Priorities	CR
Availability (A)	1	4	1	0,4444	
Productivity (P)	1/4	1	1/4	0,1111	0
Output quality (OQ)	1	4	1	0,4444	

Table 3.4: Pairwise comparisons of functional and technical aspects.

F&T objectives	MQ	A	R	M	OEE	P	OQ	Priorities	CR
Maintenance quality (MQ)	1	1/5	1/5	2	1/7	1/3	1/6	0,0366	
Availability (A)	5	1	3	7	1/2	3	1/2	0,1984	
Reliability (R)	5	1/3	1	4	1	1	1/3	0,1217	
Maintainability (M)	1/2	1/7	1/4	1	1/6	1/3	1/7	0,0292	0,0460
OEE	7	2	1	6	1	4	1/2	0,2246	
Productivity (P)	3	1/3	1	3	1/4	1	1/4	0,0814	
Output quality (OQ)	6	2	3	7	2	4	1	0,3081	

Table 3.5: Pairwise comparison of functional and technical aspects with respect to maintenance costs.

Maintenance costs	MQ	A	R	M	OEE	P	OQ	Priorities	CR
Maintenance quality (MQ)	1	1/7	1/7	2	1/5	1/4	1/3	0,0358	
Availability (A)	7	1	2	8	3	4	3	0,3375	
Reliability (R)	7	1/2	1	7	2	3	2	0,2280	
Maintainability (M)	1/2	1/8	1/7	1	1/8	1/7	1/7	0,0230	0,0332
OEE	5	1/3	1/2	8	1	2	1	0,1461	
Productivity (P)	4	1/4	1/3	7	1/2	1	1/2	0,0964	
Output quality (OQ)	3	1/3	1/2	7	1	2	1	0,1331	

a positive multiplicative constant (thus defining a ratio scale), and made unique through normalization, is the only plausible candidate for representing priorities derived from a positive reciprocal near consistent pairwise comparison matrix." Consequently, the principal eigenvector method, proposed by Saaty, will be used in this chapter to derive priorities from pairwise comparison matrices. The local priority vector is computed as the unique solution to:

$$A\omega = \lambda_{max}\omega \tag{3.1}$$

Where A is defined as the matrix of pairwise comparison values (e.g. Table 3.2 - 3.5); ω is the priority vector, also called principal eigenvector and λ_{max} is the maximum or principal eigenvalue of matrix A. The principal eigenvector represents the priority rating of each element in the pairwise comparison matrix. This eigenvector becomes the local priority vector when normalized. For each pairwise comparison matrix an associated local priority vector is calculated. The derived local priority vectors for the pairwise comparison matrices are shown in Table 3.2 - 3.5.

When a reciprocal matrix of comparisons $A = (a_{ij})$ is considered, where $a_{ij}(a_{ij} = \omega_i/\omega_j)$ represents the importance of element i over element j and a_{jk} represents the importance of element j over k, then a_{ik}, the importance of element i over k, must equal $a_{ij}.a_{jk}$ to have consistent judgments. Of course this is almost never the case when performing pairwise comparisons. For this reason a consistency check of the judgments of the decision makers, through calculating the consistency ratio, is done. This consistency ratio checks if the judgments of the decision makers follow the logic, rather than filling in random numbers. Lack of consistency in the pairwise comparisons indicates lack of understanding of the problem by the decision makers, which leads to wrong decisions. The consistency ratio is defined by:

$$CR = \frac{CI}{RI} \; with \; CI = \frac{\lambda_{max} - n}{n - 1} \tag{3.2}$$

Where CR is defined as the Consistency Ratio, CI is the Consistency Index and RI is the Random Index (Saaty 1990). n is the size of matrix A. The consistency ratio of each pairwise comparison matrix is calculated using the above formula and shown in Table 3.2 - 3.5. A consistency ratio of less than 0.10 or 10% is acceptable (Saaty 1990). In case of higher CR the decision makers need to be consulted again to fine-tune their pairwise comparisons.

Step 5. Supermatrix formation and overall priority calculation

A supermatrix is a two-dimensional matrix that consists of all elements of the different clusters (rows and columns). The supermatrix represents the influence priority of an element at the left of the matrix (row) on an element at the top of the matrix (column). Each local priority vector derived from the pairwise comparison matrices (cfr. Table 3.2 - 3.5) is inserted at the right column of the supermatrix. Generally each column of this matrix is not normalized or equal to one, which makes this matrix the un-weighted supermatrix which is shown in Table 3.6.

For convergence to occur, the supermatrix needs to be column stochastic. After normalization the weighted supermatrix is formed. The final step in obtaining the global priority vector is reaching synthesis by raising the weighted supermatrix to large powers as follows:

$$\begin{gathered} W_{limit} = \lim_{x \to \infty} (W_{weighted})^2 \; or \; (W_{weighted})^{2k+1}, \\ where\ k\ is\ an\ arbitrarily\ large\ number \end{gathered} \tag{3.3}$$

Raising the weighted supermatrix to these large powers is necessary to reach stabilization or convergence (i.e. the values in the supermatrix do not change anymore when the matrix is multiplied by itself). The resulting matrix is the limit supermatrix shown in Table 3.7, which contains the global priority vector. The reason why the supermatrix is raised to large powers is to synthesize all transitive relationships between clusters and elements in the network structure. In this way all effects of interdependence in the network are reflected in the global priority vector.

3.3.3 Case study results: business specific maintenance objectives

Determining the business specific maintenance objectives (i.e. step 2 of the proposed methodology in Section 3.2.1) is performed for all five case studies based on the described ANP methodology. The business specific maintenance objectives are defined as the maintenance objectives with the highest priorities derived from the application of the ANP methodology. The results (i.e. limit priorities) are shown in Figure 3.5.

Looking into detail to the results of Figure 3.5 for each case study separately, the following conclusions can be drawn. For *company A* (i.e. manufacturer of

Table 3.6: Un-weighted supermatrix for company D.

	Goal	MB	F&T	PDL	S	P&E	MC	MQ	A	R	M	OEE	P	OQ	CRD	LCO	I	L	EI	SRH	PM
Goal	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Maintenance budget (MB)	0,037	0,000	0,201	0,121	0,111	0,075	0,269	0,156	0,061	0,064	0,059	0,070	0,059	0,059	0,186	0,136	0,068	0,111	0,079	0,056	0,061
Functional and technical aspects (F&T)	0,256	0,288	0,000	0,375	0,464	0,540	0,255	0,426	0,310	0,395	0,340	0,355	0,325	0,398	0,198	0,223	0,259	0,107	0,162	0,174	0,200
Plant design life (PDL)	0,168	0,115	0,238	0,000	0,121	0,246	0,135	0,071	0,142	0,241	0,103	0,192	0,115	0,171	0,361	0,395	0,056	0,111	0,120	0,097	0,106
Support (S)	0,063	0,080	0,069	0,066	0,000	0,139	0,072	0,135	0,298	0,108	0,107	0,192	0,154	0,091	0,058	0,062	0,447	0,554	0,116	0,097	0,185
People and environment (P&E)	0,476	0,517	0,492	0,438	0,304	0,000	0,269	0,211	0,189	0,192	0,391	0,192	0,347	0,280	0,198	0,184	0,170	0,117	0,524	0,575	0,448
Maintenance costs (MC)	0,000	1,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Maintenance quality (MQ)	0,000	0,000	0,037	0,000	0,000	0,000	0,036	0,000	0,000	0,333	0,000	0,000	0,000	0,000	0,000	0,000	0,087	0,000	0,000	0,047	0,000
Availability (A)	0,000	0,000	0,198	0,000	0,000	0,000	0,338	0,000	0,000	0,000	0,000	0,444	0,000	0,000	0,203	0,000	0,448	0,000	0,000	0,196	0,000
Reliability (R)	0,000	0,000	0,122	0,000	0,000	0,000	0,228	0,000	0,875	0,000	0,000	0,000	0,000	0,000	0,175	0,000	0,413	0,000	0,000	0,271	0,000
Maintainability (M)	0,000	0,000	0,029	0,000	0,000	0,000	0,023	0,000	0,125	0,000	0,000	0,000	0,000	0,000	0,035	0,000	0,052	0,000	0,000	0,077	0,000
OEE	0,000	0,000	0,225	0,000	0,000	0,000	0,146	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,101	0,000	0,000	0,000	0,000	0,000	0,000
Productivity (P)	0,000	0,000	0,081	0,000	0,000	0,000	0,096	0,000	0,000	0,000	0,000	0,111	0,000	0,000	0,068	0,000	0,000	0,000	0,000	0,000	0,000
Output quality (OQ)	0,000	0,000	0,308	0,000	0,000	0,000	0,133	0,000	0,000	0,667	0,000	0,444	0,000	0,000	0,418	0,000	0,000	0,000	0,000	0,409	0,000
Capital replacement decisions (CRD)	0,000	0,000	0,000	0,800	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Life-cycle optimization (LCO)	0,000	0,000	0,000	0,200	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Inventory of spare parts (I)	0,000	0,000	0,000	0,000	0,750	0,000	0,667	0,000	0,667	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Logistics (L)	0,000	0,000	0,000	0,000	0,250	0,000	0,333	0,000	0,333	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Environmental impact (EI)	0,000	0,000	0,000	0,000	0,000	0,088	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,875	0,000	0,000	0,000	0,000	0,000	0,000
Safety/risk/health (SRH)	0,000	0,000	0,000	0,000	0,000	0,773	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,125	0,000	0,000	0,000	0,000	0,000	0,000
Personnel management (PM)	0,000	0,000	0,000	0,000	0,000	0,139	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000

Table 3.7: Limit supermatrix for company D.

	Goal	MB	F&T	PDL	S	P&E	MC	MQ	A	R	M	OEE	P	OQ	CRD	LCO	I	L	EI	SRH	PM
Goal	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Maintenance budget (MB)	0,057	0,057	0,057	0,057	0,057	0,057	0,057	0,057	0,057	0,057	0,057	0,057	0,057	0,057	0,057	0,057	0,057	0,057	0,057	0,057	0,057
Functional and technical aspects (F&T)	0,169	0,169	0,169	0,169	0,169	0,169	0,169	0,169	0,169	0,169	0,169	0,169	0,169	0,169	0,169	0,169	0,169	0,169	0,169	0,169	0,169
Plant design life (PDL)	0,092	0,092	0,092	0,092	0,092	0,092	0,092	0,092	0,092	0,092	0,092	0,092	0,092	0,092	0,092	0,092	0,092	0,092	0,092	0,092	0,092
Support (S)	0,071	0,071	0,071	0,071	0,071	0,071	0,071	0,071	0,071	0,071	0,071	0,071	0,071	0,071	0,071	0,071	0,071	0,071	0,071	0,071	0,071
People and environment (P&E)	0,171	0,171	0,171	0,171	0,171	0,171	0,171	0,171	0,171	0,171	0,171	0,171	0,171	0,171	0,171	0,171	0,171	0,171	0,171	0,171	0,171
Maintenance costs (MC)	0,028	0,028	0,028	0,028	0,028	0,028	0,028	0,028	0,028	0,028	0,028	0,028	0,028	0,028	0,028	0,028	0,028	0,028	0,028	0,028	0,028
Maintenance quality (MQ)	0,014	0,014	0,014	0,014	0,014	0,014	0,014	0,014	0,014	0,014	0,014	0,014	0,014	0,014	0,014	0,014	0,014	0,014	0,014	0,014	0,014
Availability (A)	0,043	0,043	0,043	0,043	0,043	0,043	0,043	0,043	0,043	0,043	0,043	0,043	0,043	0,043	0,043	0,043	0,043	0,043	0,043	0,043	0,043
Reliability (R)	0,045	0,045	0,045	0,045	0,045	0,045	0,045	0,045	0,045	0,045	0,045	0,045	0,045	0,045	0,045	0,045	0,045	0,045	0,045	0,045	0,045
Maintainability (M)	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009
OEE	0,022	0,022	0,022	0,022	0,022	0,022	0,022	0,022	0,022	0,022	0,022	0,022	0,022	0,022	0,022	0,022	0,022	0,022	0,022	0,022	0,022
Productivity (P)	0,010	0,010	0,010	0,010	0,010	0,010	0,010	0,010	0,010	0,010	0,010	0,010	0,010	0,010	0,010	0,010	0,010	0,010	0,010	0,010	0,010
Output quality (OQ)	0,066	0,066	0,066	0,066	0,066	0,066	0,066	0,066	0,066	0,066	0,066	0,066	0,066	0,066	0,066	0,066	0,066	0,066	0,066	0,066	0,066
Capital replacement decisions (CRD)	0,037	0,037	0,037	0,037	0,037	0,037	0,037	0,037	0,037	0,037	0,037	0,037	0,037	0,037	0,037	0,037	0,037	0,037	0,037	0,037	0,037
Life-cycle optimization (LCO)	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009	0,009
Inventory of spare parts (I)	0,042	0,042	0,042	0,042	0,042	0,042	0,042	0,042	0,042	0,042	0,042	0,042	0,042	0,042	0,042	0,042	0,042	0,042	0,042	0,042	0,042
Logistics (L)	0,017	0,017	0,017	0,017	0,017	0,017	0,017	0,017	0,017	0,017	0,017	0,017	0,017	0,017	0,017	0,017	0,017	0,017	0,017	0,017	0,017
Environmental impact (EI)	0,018	0,018	0,018	0,018	0,018	0,018	0,018	0,018	0,018	0,018	0,018	0,018	0,018	0,018	0,018	0,018	0,018	0,018	0,018	0,018	0,018
Safety/risk/health (SRH)	0,068	0,068	0,068	0,068	0,068	0,068	0,068	0,068	0,068	0,068	0,068	0,068	0,068	0,068	0,068	0,068	0,068	0,068	0,068	0,068	0,068
Personnel management (PM)	0,012	0,012	0,012	0,012	0,012	0,012	0,012	0,012	0,012	0,012	0,012	0,012	0,012	0,012	0,012	0,012	0,012	0,012	0,012	0,012	0,012

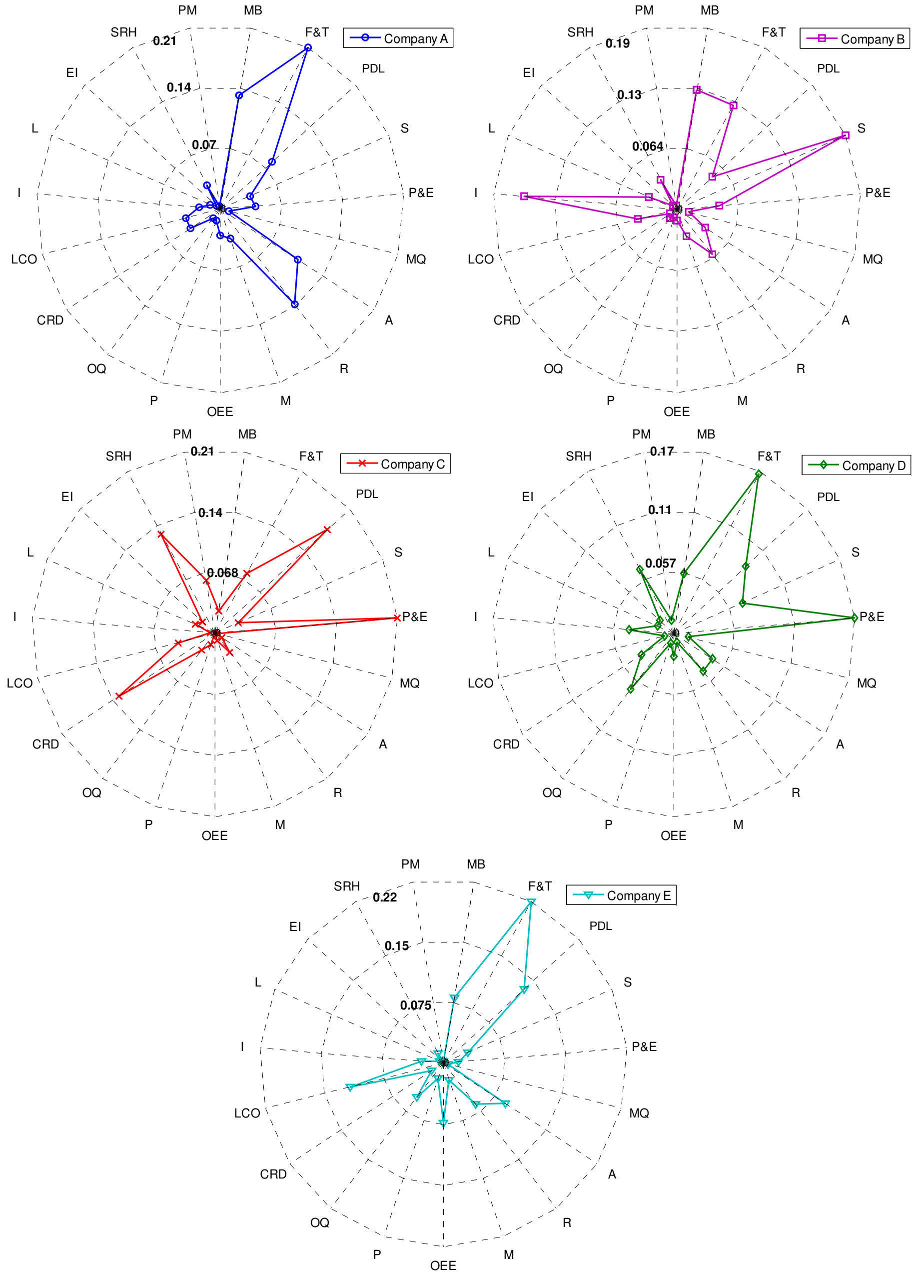

Figure 3.5: Comparison of limit priorities for all five case studies.

wind turbine components) it is clear that “functional and technical aspects” together with the “maintenance budget” are the most important maintenance objectives at the strategic decision level. Looking into detail to the tactical level objectives makes clear that achieving high reliability and availability of the components by the right maintenance strategy and policy is crucial. This is the case because next to the influence of availability and reliability on the functional and technical aspects, they also influence the maintenance costs. High availability is necessary to reduce high downtime penalties, while high reliability is wanted to limit the number of maintenance actions on the wind turbine components. Limiting these maintenance actions is essential in reducing the high costs of equipment (e.g. cranes) and transport (e.g. vessels), which is certainly the case for an offshore wind turbine due to the difficult accessibility and uncontrollable weather conditions. Another remarkable observation is that the strategic “design life” objective (i.e. further subdivided in life cycle optimization and capital replacement decisions on the tactical level) is scored relatively high, while this comprises long term decisions which are normally not directly related to maintenance management in most cases. For a wind turbine component manufacturer this is however an essential condition to stay in front of the competition in the fast evolving wind energy sector. Moreover, when design faults are made, which is not uncommon in a new field like wind industry, decisions about design changes (i.e. life cycle optimization or capital replacement) have an important effect on the total maintenance costs. For *company B* (i.e. manufacturer of industrial systems and provider of additional service contract) the results show that providing maintenance “support” to their industrial customers is the major maintenance objective on the strategic level because of the inclusion of the additional service contract in their offering. In order to achieve this, management of the inventory of spare parts is crucial. This is the case because the logistic time to service a customer is mainly determined by the availability of spare parts. This also has further implications on other maintenance objectives like for example the maintenance cost, as when no spare parts are available the downtime cost accrued becomes very high. Like expected for *company C* (i.e. medium size hospital), the results give a totally different view on which maintenance objectives are important due to the different business environment. It is clear that “people and environment” on the strategic level, and safety, risk and health on the tactical level are the essential maintenance objectives for the hospital. This is not a surprise because maintenance as a tool to ensure patient safety is the most important goal in a hospital environment. Moreover, this case study illustrates that the methodology is customizable to the business environment, as company C did not have any experience with OEE as a measure or maintenance objective, so it was dropped from the analysis (i.e. priority is zero). The results for *company D* (i.e. large university hospital) are similar to the results for company C. This means that "people and environment" on the strategic level, and safety, risk and health on the tactical level are the essential maintenance objectives. This was to be expected as both environments are very similar. However, these results also provide a validation of the developed methodology as organizations with a similar business environment should consider the same maintenance objectives as important. Furthermore, company D considers output quality as an important tactical maintenance objective because all medical equipment should work according to specifications. This also has a direct influence on patient safety and health. Mark that maintenance budget and costs do not play a crucial role in maintenance management for a hospital environment (i.e. company C and D), as in the first place the health of the patient should be guaranteed no matter how high the consequential costs. For *company E* the most important strategic maintenance objectives are "functional and technical aspects" and reach or extend the "design life" of the considered system. For a military system the functionality (i.e. availability and reliability on tactical level) is crucial, as these systems are operated in extreme conditions and no standard flight profile can be implemented. Moreover, failure of the system in a battle situation can be literally deadly. The optimization and extension of the lifetime of military systems is very important as these systems are very costly to replace and many possible upgrades are possible during the life cycle of the system.

From the case study results it can be concluded that each business sector has its specific maintenance objectives on different organizational levels which define their maintenance strategy. Acknowledgment of this is crucial for the right implementation and application of an MPM system. Correspondingly, each business environment needs different MPI on all organizational levels in order to measure maintenance performance in an adequate manner. This is like expected and illustrates the importance of a methodological approach to select business specific MPI based on the corporate strategy and derived maintenance objectives. The proposed methodology in this chapter addresses this need by guiding and supporting maintenance decision makers in identifying business specific maintenance objectives.

3.4 Determination and performance monitoring of MPI

Based on the previously determined business specific maintenance objectives (i.e. the ones with high priority), the corresponding MPI directly linked to the maintenance objectives should be derived for all organizational levels (i.e. step 3 of the proposed methodology in Section 3.2.1). In this way business specific MPI are derived. In order to illustrate the approach on how this can be done, the case study on company E is extended to include the derivation of business specific MPI for the "functional and technical aspects" cluster, as this is the most important maintenance objective according to the results shown in Figure 3.5. Note that the same methodology is valid to derive MPI for other maintenance objectives and even other case studies.

The example demonstrates the derivation of MPI in relation to the real maintenance objectives on the different organizational levels of a company. The objective of the case study for company E is to derive MPI for work order performance evaluation. The network structure (derived from the generic ANP network structure (Figure 3.4)) and corresponding priorities for the maintenance objectives (i.e. Figure 3.5) derived by the presented ANP methodology are given in Figure 3.6. Based on the defined maintenance objectives, the corresponding business specific MPI can be derived for all organizational levels by starting at the operational level (i.e. bottom–up approach of Section 3.2.1). By means of an example only one objective is monitored on the operational level (Figure 3.6). Therefore, this also directly reflects the performance on the tactical level. It is however straightforward to aggregate (i.e. based on their relative weight) multiple measures on the operational level, when available (i.e. Figure 3.2), into an MPI on the tactical management level and finally on the strategic level.

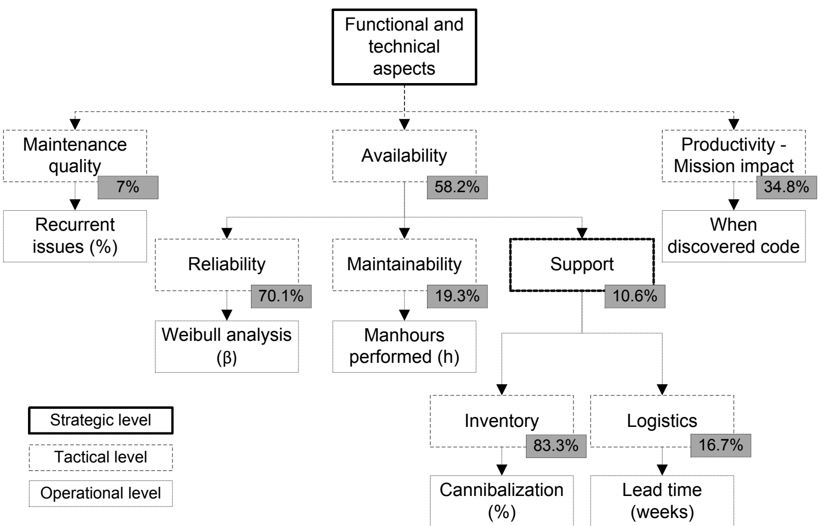

Figure 3.6: Network structure, priorities for the maintenance objectives and MPI of the "functional and technical aspects" cluster for company E.

Based on the defined network structure of Figure 3.6, which can be seen as a customized MPM system for company E, it is possible to evaluate maintenance performance on all organizational levels. For company E this is done by defining three classes of maintenance performance for each MPI on the operational level (Table 3.8). The classes are defined based on historical data, and the limits are defined according to the rule that 25% of the current work orders are class 1, 75% are class 2 and the others are class 3. Class 1 means excellent performance while class 3 means major performance improvement possible. Based on the MPI performance on the operational level, it is possible to derive MPI and maintenance performance on the tactical and strategic level by aggregation through the network structure of Figure 3.6. Equation 3.4 illustrates a possible implementation of this approach and indicates maintenance performance on all organizational levels. The operational performance of each work order is determined by classification based on Table 3.8. Finally, by aggregation through the network structure one strategic performance measure for the "functional and technical aspects" cluster is obtained. This makes that maintenance performance can be reflected by one MPI on the corporate level. Maintenance managers benefit from this as they do not lose track on performance due to the definition of too many and cumbersome MPI. On the other side, aggregation of MPI on lower levels (i.e. operational level) to the higher levels (i.e. tactical and strategic level) can make it difficult to know what is exactly happening. However, the applied ANP approach and defined network structure (Figure 3.6) make it possible to investigate deviations of performance on lower levels of the organizational structure. Moreover, if a corporate indicator shows a problem in performance, then the lower levels can clarify and define the cause in a straightforward way. A business specific MPM system considering all organizational levels is thus implemented by the application of the developed MPM framework and ANP model.

$$\begin{aligned}
&\overbrace{(\overbrace{((1 \times 0.833) + (2 \times 0.167)) \times 0.106}^{\text{support}} + \overbrace{(3 \times 0.193)}^{\text{maintainability}} + \overbrace{(1 \times 0.701)}^{\text{reliability}}) \times 0.582}^{\text{availability}} \\
&\quad + \overbrace{(3 \times 0.07)}^{\text{maint. qual.}} + \overbrace{(1 \times 0.348)}^{\text{mission impact}} = 1.0618
\end{aligned} \tag{3.4}$$

Table 3.8: Maintenance performance classification for MPI on the operational level.

Maintenance objective	MPI	Class 1	Class 2	Class 3
Recurrent issues (%)	Recurrent failure after repair (%)	$< 5\%$	$< 10\%$	$> 10\%$
Weibull analysis (β)	Failure rate (shape parameter β)	$< 0{,}8$	$< 1{,}2$	$> 1{,}2$
MTTR (h)	Manhours performed (h)	$<$ 4h	$<$ 12h	$>$ 12h
When Discovered Code (WDC)	Operational impact of a failure: I = in flight, B = before flight, A = abort, N = no abort, D = delay	IN,BN	BD	IA,BA
Cannibalization (%)	Cannibalization of spare parts from other system (%)	$< 10\%$	$< 20\%$	$> 20\%$
Lead time (weeks)	Spare parts lead time (weeks)	$<$ 1 week	$<$ 4 weeks	$>$ 4 weeks

3.5 Discussion and managerial implications

In this section we discuss the conclusions derived from the case study results in terms of the proposed methodology and its managerial implications. For the purpose of research validation and verification the feedback of the decision makers on the proposed methodology is discussed. Finally, we discuss some limitations of the methodology and propose some directions for future research.

A methodological approach to develop a business specific MPM system is presented. From the many discussions within the frame of the performed case studies, the development of a methodological and structured model to derive a business specific MPM system is perceived as a major contribution, as both in industry and academic research this was missing. The proposed methodology assists decision makers in developing a customized MPM system by addressing the two major flaws identified in the currently available MPM frameworks and models. All organizational levels of a company are addressed while directly linking monitored MPI to the relevant maintenance objectives. These properties are identified within the performed case studies as the major advantages of the proposed methodology. Decision makers are able to get an overview of performance on each management level. This also means that people working on different management levels within the company have their own customized performance indicators. Consequently, the number of MPI and objectives monitored is limited by application of the methodology. This improves the manageability on each organizational level compared to the long lists of MPI currently available in industry and literature. The development of the MPM system and ANP model aligns the maintenance objectives on all management levels with the relevant MPI used. It supports maintenance managers in deriving a customized MPM system by translating maintenance objectives to relevant MPI on all organizational levels.

The presented ANP methodology provides for simplification of a complex multi-criteria decision problem. The case studies show that the ANP approach provides a solution to the problem of MPM system definition. The major advantage, mentioned by the decision makers, is the capability of handling complex decision problems with interdependencies between the decision criteria. As without the ANP methodology it would be a very challenging, if not impossible, task to account for all interdependencies in the decision problem. Furthermore, the pairwise comparisons provide insight into the decision problem, which leads to more informed decision making. Finally, the interpretation of the results (i.e. priorities) of the ANP approach is straightforward and unambiguously. It needs to be emphasized that despite the many advantages, care must be taken in the application of the ANP approach. For example, sometimes the decision makers encountered difficulties to express preference by the defined ratio scale. The possibility of incorporating a fuzzy scale into the ANP approach was given as a possible solution to this problem of defining crisp numbers to express preference. Another remark was that the biasing of the decision maker cannot be ruled out. To avoid such situations, group decision making methods like consensus should be used. Moreover, sharing of ideas and insights often lead to a better understanding of the decision problem.

The first step in the proposed methodology is the definition of a generic MPM system. This task is performed by the authors by developing a generic MPM system in the form of a generic network structure. This resulted in a considerable reduction of total effort needed to apply the entire methodology to the case studies. This was also acknowledged by the decision makers in the different case studies. The advantage is that this generic network structure directly assists the decision maker by offering a starting point for defining a customized network structure. Note that despite the advantage in the effort necessary; some flexibility could possibly be lost because the generic network structure could bias the decision maker in customizing the MPM system/network structure in the decision problem. It could direct the decision maker towards a predefined problem structure. Starting from scratch to construct the network structure would overcome this issue, but a major effort would be necessary. Sensitivity analysis can be used to investigate the effect of possibly biased decisions. A trade-off should be made between the risk to take a biased decision and the effort one wants to put into the development of a network structure. However, it has to be marked that the general structure of the generic network structure was never changed and that only relations and criteria were dropped, not added, to form the customized network structure for the considered case studies. This strengthens the belief of the authors that the presented network structure is generic and forms a solid base to derive a business specific network structure.

Finally, several directions for further research are identified. The developed methodology is usable as a comparison tool between different business sectors and environments, which makes benchmarking between and within different business environments possible. Furthermore, it is interesting to investigate how the concept of e-maintenance can assist on the implementation of an MPM system and the measurement of MPI. Moreover, it is valuable to investigate if the developed methodology can be applied as a decision support tool to make comparisons, based on the defined priorities in the network structure, between different maintenance strategy and/or policy alternatives (i.e. this is subject of the following chapters). In this way the MPM system can be linked to particular maintenance strategies and their performance. This makes comparison of their efficiency and effectiveness possible in order to determine the best maintenance strategy and/or policy for a specific case.

The proposed methodology may require significant effort and time from the decision makers, so possibilities to reduce this could be subject of further research as well. As consensus is more desirable at higher management levels of the ANP model (i.e. because of the higher priorities) the decision problem could be split into several sub-problems in order to reduce the effort. For example, on the operational and tactical management level only one expert could be appointed, while the pairwise comparisons at the strategic level are still performed by group decision making in order to avoid bias on the higher management levels. This approach would take advantage of the proposed problem structure that considers all organizational levels. Yet, regardless the effort in developing an MPM system, a structured methodology like proposed in this chapter may help to reduce the risk of poor decisions considerably.

3.6 Conclusions

A comprehensive methodology, based on the analytic network process (ANP), to determine and prioritize business specific maintenance objectives and corresponding MPI from a generic maintenance objective network structure is presented. The developed methodology directly addresses the first research question (Section 1.6.1) of this dissertation. Moreover, by providing decision support and guidance on the implementation of a customized MPM system, the two major flaws within currently available MPM frameworks are addressed. By considering all organizational levels (i.e. strategic, tactical and operational level) corporate as well as operational maintenance objectives and corresponding MPI are defined. The development of the MPM system and ANP model aligns the maintenance objectives on all management levels with the relevant MPI used. It supports maintenance managers in translating maintenance objectives to relevant MPI, starting at the operational level and aggregating these to form MPI at the corporate level in order to create value for the entire organization. In this way the defined MPI are aligned with the organizational structure of the company. The result is a business specific MPM system usable throughout the entire company. The methodology presented in this chapter is illustrated and validated by the application to five extensive case studies. The results of these case studies endorse the importance of customization of the implemented MPM system to fit the specific business environment. Furthermore, they illustrate the importance of a methodological approach to select business specific MPI based on the specific maintenance objectives and corporate strategy.

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Chapter 4

Quantifying the added value of an imperfectly performing condition monitoring system - application to a wind turbine gearbox

As already discussed in the definition of the second research question in Section 1.6.2, there exist two major types of models for predictive maintenance based on the targeted output and/or the availability of condition monitoring data. The first can be defined as models for long-term performance evaluation of PdM and the second as models for real-time and dynamic maintenance decision making based on condition monitoring information. The former type of model, without the necessity of condition monitoring data, is developed and applied to the specific case of a wind turbine gearbox manufacturer (i.e. *company A* of Chapter 3) in this chapter. In this way decision support is given before the real implementation of a condition monitoring system. It assists maintenance decision makers to answer the question to invest or not in condition monitoring. Implementation of a condition monitoring system is a difficult decision due to many uncertain parameters. This is certainly the case for the wind turbine

This chapter is based on A. Van Horenbeek et al. (2013d). "Quantifying the added value of an imperfectly performing condition monitoring system - application to a wind turbine gearbox". In: *Reliability Engineering & System Safety* 111, pp. 45–57 industry where factors like long logistical times and weather conditions have a major influence on the economic benefit. One of the parameters that is neglected in most of the available literature is the performance of the condition monitoring system itself. In this chapter a new concept for modeling this performance based on the P-F curve of different failure modes is presented. The concept is illustrated on an extensive case study for a gearbox of a wind turbine. A stochastic simulation model is constructed in order to quantify the economic added value of implementing an imperfectly performing condition monitoring system into a gearbox. This case study proves that a condition monitoring system generates an economic benefit compared to the currently applied maintenance strategy. However, the magnitude of this benefit depends strongly on the performance of the condition monitoring system.

4.1 Problem delineation

The importance of condition monitoring in maintenance is ever increasing in industry. Condition Monitoring Systems (CMS) can help to overcome unexpected downtime and reduce costs. This certainly applies for the wind energy sector, which is characterized by strong growth, where difficult accessibility of the turbine, high spare part costs and dependence on weather conditions forces wind turbine component manufacturers and operators to turn to condition monitoring systems. There exist several studies on how to quantify the added value of implementing a CMS in wind turbines in literature (Besnard and Bertling 2010; Nilsson and Bertling 2007; Garcia et al. 2006; Nielsen and Sørensen 2011). Most of these models assume that the state of a component can be perfectly monitored by the CMS. When looking at maintenance from a system rather than a component perspective, this is not always the case. A CMS is capable of predicting certain failure modes of different components in a system; however the CMS cannot predict every potential failure mode and costly false alarms are possible. It is thus important to take into account the effectiveness or performance of a CMS when quantifying the added value and defining the maintenance policy. The objective of this chapter is to present a quantitative approach to determine the added value of a CMS based on a static, stochastic model with Monte Carlo simulations, taking into account the performance of the CMS and the potential development of secondary damage. In this chapter the P-F curve (Moubray 1997), where the point in time where an indication of deterioration of the component can be detected is referred to as a potential failure ‘P’ and the point in time where the component suffers critical failure is referred to as functional failure ‘F’, is used to model the performance of a CMS on different failure modes. Consequently a system level perspective is taken. The theoretical approach is illustrated by a case study of a gearbox in an onshore wind turbine. The economic benefit of implementing a CMS in an onshore wind turbine gearbox, from the point of view of the gearbox manufacturer, is determined. The economic benefit is determined by incorporating the most important objectives (i.e. maintenance cost, reliability and availability) as derived in Section 3.3.3 by application of the presented ANP methodology in Chapter 3. This case study illustrates the importance of incorporating the performance of the CMS into the calculation of the added value of a CMS, which is the major contribution.

4.1.1 Condition monitoring system performance

Many optimization models for condition-based maintenance are described in literature illustrating the economic benefit of implementing condition monitoring (Grall, Bérenguer, et al. 2002; Grall, Dieulle, et al. 2002; Barata et al. 2002; Jardine, D. Lin, et al. 2006; Marseguerra, Zio, and Podofillini 2002; van der Weide et al. 2010; Bouvard et al. 2011). These assume that the degradation process of each considered component can be determined by different monitoring techniques (e.g. vibration monitoring, oil analysis). Based on this degradation process, decisions (e.g. time of inspection, time of maintenance) to achieve optimal maintenance are made. However, when realistically modeling such facilities a system perspective should be taken. It is not cost effective to accommodate every component in a production machine with its specific monitoring system. Therefore, condition monitoring systems (CMS) exist which are capable of monitoring different components and failure modes simultaneously. It is important to take into account the performance of the CMS, the ability to detect a failure mode and at what stage of deterioration it can be detected, when determining the added value of condition monitoring because the performance on each failure mode is not perfect. This determines the time to react to the potential failure of a component, which determines the ability to avoid long downtimes of the equipment by the possibility of planning maintenance actions in advance and preventing corrective maintenance actions. Preventing secondary damage on other components by detecting an incipient failure is another advantage of implementing a CMS. Also this benefit is dependent on the time when the CMS is capable of detecting a potential failure. The earlier the CMS detects the deterioration propagation, the less secondary damage will occur. A concept that is often used to describe the deterioration process of a component and the performance of on-condition maintenance tasks is the P-F curve and P-F interval (Moubray 1997). Directly related to this concept is the proposed delay time model of Christer and Waller (1984).

A balance between the performance and cost of the CMS should be found. This is certainly the case for critical machinery with a short P-F interval or long logistical waiting time (e.g. for spare parts). When the CMS only detects the failure in a late stage of the deterioration process, no time is left to react to the failure propagation and this results in costly corrective maintenance with potential secondary effects on other components. For this reason, the performance of a CMS and potential secondary damage propagation should be taken into account to really determine the added value of implementing condition-based maintenance. In this chapter this will be addressed by using the well known P-F curve.

4.1.2 Condition monitoring systems for wind turbines

In the wind turbine industry the implementation of condition-based maintenance is intensively debated today. The time of performing a maintenance action on a wind turbine is dependent on several uncertain factors (e.g. weather conditions, availability of lifting equipment), which causes long logistical waiting times and possible consequential damage. This is certainly the case for offshore wind turbines, which makes condition monitoring tools and maintenance scheduling especially important for offshore applications. Together with the performance of the CMS, these factors play a crucial role in determining the added value. In reference (Hameed et al. 2010) the importance of CMS performance and prevention of secondary damage is mentioned, but no methodology to model those is proposed. Wiggelinkhuizen et al. (2008) derive three major requirements of a CMS; detection of failure mechanism, detection on time and measurable health criteria. Based on these requirements the performance of different condition monitoring systems is given. The performance is the potential of the CMS to move failure modes to lower failure repair classes which reduces the effect of failure. The impact of the effectiveness of a CMS on the economic benefit is also evaluated by McMillan and Ault (2007). A CMS effectiveness probability is introduced, which is a measure of how likely the CMS is to detect and diagnose a developing failure successfully. Nielsen and Sørensen (2011) introduce a probability of detection, which models the reliability of an inspection on the wind turbine component. The probability of detection is directly linked to the damage level of the component. Although the importance of CMS effectiveness or performance is stated in these references, the CMS performance is never linked to the real deterioration process of a component, or is limited to a single component. In this chapter these shortcomings are remediated by linking the CMS performance to the P-F curve of several components, which approximates the deterioration process of a component or system. Based on a life cycle cost (LCC) approach the added value of a CMS is determined for a case study on a wind turbine gearbox.

4.1.3 Contributions to state-of-the-art

The major contributions of the developed model in this chapter can be summarized as follows:

- A methodology, based on the well known P-F curve, is presented to model imperfect maintenance of a CMS and potential secondary damage. The performance of the CMS and secondary damage propagation are directly linked to the degradation and the corresponding P-F curve of the component.
- A methodology to quantify the added value on the long-term of an imperfectly performing CMS is described. Moreover, the model is applicable to both cases where condition monitoring information is available and where it is not. The model is able to determine the minimal performance of a CMS necessary to generate economic value.
- The methodology is applied to an extensive case study of a wind turbine gearbox, hereby directly addressing the formulated problem of applicability of maintenance optimization models (Section 1.4).
- The results show the importance of the inclusion of imperfect performance and secondary damage in order to correctly evaluate the added value of CMS implementation.

In Section 4.2 the theoretical model on how the performance of the CMS and consequential damage propagation is modeled, based on the P-F curve, is presented. In Section 4.3 the theoretical approach is fitted to a real-life case study of an onshore wind turbine gearbox in order to illustrate the developed model. The results of this case study are given in Section 4.4 and finally future work and conclusions are stated in Section 4.5.

4.2 Theoretical model

In Section 4.2.1 to 4.2.3 the developed theoretical model representing the performance of a CMS and the deterioration process of components, based on the P-F curve, is presented. Consequently the utilized approach to model the effect of secondary or consequential damage is discussed in Section 4.2.4.

4.2.1 The P-F curve

Moubray (1997) examined failure patterns that can be detected by condition monitoring and highlights the importance of the P-F curve and P-F interval (Figure 4.1). This curve visualizes the deterioration in time of a particular component. When a component is operated, it will start to deteriorate until it completely loses its capability to carry out its function. The point in time where the component suffers critical failure is referred to as functional failure 'F'. A component can perform its regular task just up to this point. The point in time where an indication of deterioration of the component can be detected is referred to as a potential failure 'P'. The time between point P and F is called P-F interval. Directly related to the concept of the P-F curve introduced by Moubray is the delay time model proposed by Christer and Waller (1984). The central concept in this approach is the delay time of a fault, which is defined as the time lapse from when a fault could first be noticed until the time when its repair can be delayed no longer because of component failure. The time between P and F, as defined by Moubray (1997), is thus generally the same as the delay time defined by Christer and Waller (1984). It has proven possible to obtain a subjective estimate of the probability density function of the delay time, which enables the construction of models to determine the relation between a maintenance policy and consequence variables like, for example, the expected cost per unit time.

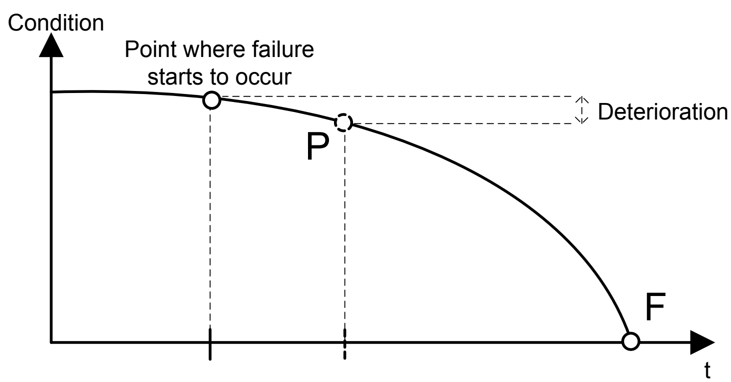

Figure 4.1: P-F curve.

The philosophy behind condition-based (CBM) and predictive maintenance (PdM) is to detect a failure in the P-F interval by using condition measurements, either continuously monitored or according to inspection intervals. This curve is the basis for determining the optimal time interval between two inspections in case of a CBM or PdM policy where condition monitoring is done according to fixed time intervals. Moreover, optimal maintenance actions and timing are determined based on the deterioration process described by the P-F curve. Besides the determination of an optimal maintenance policy, the P-F curve also gives a clear insight in the possible return on investment of a CMS. The sooner a potential failure is detected by a CMS, the smaller the component's suffered deterioration will be. Depending on the P-F interval of the component an appropriate action, based on the readings of the CMS, can be carried out. As stated earlier, the performance of the CMS is crucial in determining the added value of condition monitoring, as will be shown in the next sections of this chapter.

4.2.2 Modeling CMS performance

The performance of a CMS is determined by two interrelated parameters, γ and η:

- γ = detectability (%); this parameter represents the probability that a certain failure is detected by the CMS.
- η = efficiency (%); this parameter represents the spot on the P-F curve where the failure is detected by the CMS.

Both parameters are related in such a way that the probability of detection (detectability γ) increases with time as the condition of the considered component is deteriorating. As an example, a linear relation between efficiency η and detectability γ is given in Figure 4.2b, however, the shape of the curve can take different forms (e.g. Nielsen and Sørensen (2011)). The exact form of this relation is defined by the CMS performance for the different monitored failure modes and the underlying degradation process. In this way a direct relation between the CMS performance parameters γ and η and the component condition or deterioration is defined (Figure 4.1). An efficiency $\eta = 100\%$ corresponds to the point on the P-F curve where an indication of deterioration can first be detected. This is referred to as potential failure or point P. An efficiency $\eta = 0\%$ is the point on the P-F curve where the developing failure has led to a functional failure of the component or point F on the curve. At this point any functioning of the component is impossible. Consider for example a CMS where one point on the performance relation (Figure 4.2b) corresponds to $\gamma_1 = 20\%$ and $\eta = 70\%$ as illustrated in Figure 4.2. This CMS system is on average able to detect 20% of the developing failures at 70% remaining life between P and F. When $\eta = 0\%$ and $\gamma_3 = 90\%$, this means that the CMS will miss out on 10% of the failures. In other words, in 10% of the cases a corrective action will be necessary because the CMS did not detect the developing failure. This methodology allows to model an imperfectly performing CMS.

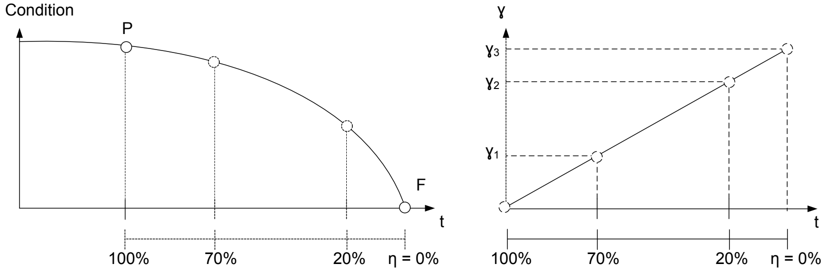

Figure 4.2: (a) Representation of parameter η on the P-F curve. (b) Relation between efficiency η and detectability γ.

For the remainder of the chapter a limiting case on the presented approach is considered. The reason for this is the fact that for the case study presented further on, no data was available on the performance relation shown in Figure 4.2b as on the moment of the study no CMS was implemented in the gearbox. Therefore, the CMS performance is modeled by a single point (γ and η), which is derived from expert knowledge, on the performance relation. This is in fact a discretized implementation of the model described in the previous paragraph. This approach describes a “worst case” scenario, as γ defines the percentage of failures detected at point η and $1 - \gamma$ defines the number of failures resolved by a corrective action (i.e. only detected at point F). As the objective of the business case is to answer the question: what is the minimal performance of the CMS to generate economic value for the gearbox manufacturer, the adopted approach remains valid. When the performance relation between γ and η is entirely known, it is however straightforward to extend the described case study with this information. The adopted approach is discussed into more detail in the following sections.

4.2.3 Modeling deterioration process and repair actions

A failure mode evolves from point P to point F on the P-F curve. To link the deterioration process of a failure mode with an appropriate repair or maintenance action, the P-F curve is divided into four deterioration categories (Figure 4.3). In this chapter the P-F curve is divided into four zones, since this corresponds well to the damage propagation of the P-F curve of the gearbox components in a wind turbine, which is used in the case study further on in this chapter. For reasons of convenience, this division will also be used to clarify the developed generic theoretical model. However, it is possible to change the number of deterioration categories according to the deterioration process that is considered. Each deterioration category requires a different repair action:

- *Category or zone A* defines the zone where the deterioration is in a very early stage and where the component damage is very limited. Minor adjustments to make the component as-good-as-new or extend the lifetime are possible.
- *Category or zone B* defines the zone where the deterioration and thus the component damage is significant, but no consequential damage is caused yet. Repair or replacement of the specific component is necessary.
- *Category or zone C* defines the zone where the deterioration has evolved up to the point where the component damage is maximal, and consequential damage is possible. Replacement of the component and eventually secondary damaged components is necessary.
- *Category or point F* defines the spot on the P-F curve where functional failure of the component has occurred. Similar as in zone C consequential damage is possible. Replacement of the component and eventually secondary damaged components is necessary.

At first sight there is no difference between detecting a potential failure in zone C or at point F. But in zone C the component is still running, although it is considerably damaged. Detecting the potential failure in zone C has the advantage that there is still some time left for planning the maintenance action, which limits the downtime, although the maintenance action itself will be the same as at functional failure (point F).

The zones of the P-F curve are separated by two threshold values $TH1$ and $TH2$. For a good comprehension of the numerical value of these thresholds, a fictive timeline t' is drawn as illustrated in Figure 4.3. This fictive timeline indicates how much time there is left from a certain point on the P-F curve to point F, the functional failure. In fact this is an indication of the remaining useful life (RUL) of the component. The values on this timeline are expressed as a percentage of the time between point P and F on the P-F curve, defined as the P-F interval. In this way zone A represents component deterioration on the P-F curve where $t' \geq TH1$, zone B represents component deterioration where $TH1 > t' \geq TH2$ and zone C represents component deterioration where $TH2 > t' > 0$. Point F represents the functional failure where $t' = 0$. The threshold values are proper to a specific failure mode.

The advantage of this representation is that the efficiency η of the CMS can be represented on the same fictive timeline t'. Earlier in this chapter, the maximum efficiency $\eta = 100\%$ was set as the point on the P-F curve where an indication of deterioration can first be detected (point P). This point coincides with the point

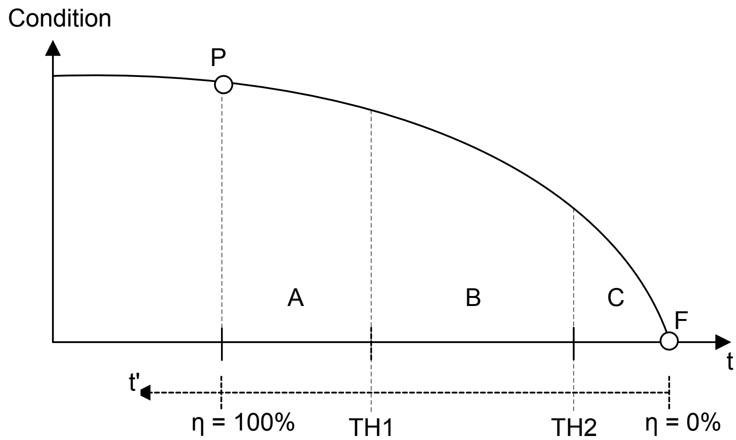

Figure 4.3: P-F curve divided by threshold $TH1$ and $TH2$ into three zones A, B and C.

on the curve where $t' = 100\%$. A similar reasoning is made for point F, where the point on the curve with minimum CMS efficiency $\eta = 0\%$ coincides with the point where $t' = 0\%$. As a result, the values for the CMS efficiency and the threshold values can be mutually compared. Note however that these concepts are totally independent. Efficiency η is a property of the CMS, while thresholds $TH1$ and $TH2$ are a property of the considered failure mode. They are only expressed on the same abscissa to make comparison possible. An example to illustrate this approach can make things clearer. Consider failure mode FM with $TH1 = 90\%$ and $TH2 = 10\%$. A CMS with efficiency $\eta = 95\%$ is capable of detecting failures on FM in zone A ($\eta \geq TH1$). A CMS with efficiency $\eta = 5\%$ is only capable of detecting a failure of FM in zone C ($TH2 > \eta > 0\%$) and thus cannot prevent maximal component damage. It should however be noted that the higher the efficiency η of the CMS, the more costly the CMS will be, as detection of damage in zone C is expected to be much easier than detection of damage in zone A. In this chapter it is assumed that the maintenance action is always initiated at the point of detection by the CMS, which is defined by η, and that the measured degradation zone perfectly matches with the real degradation zone.

Prediction of remaining useful life (RUL), which takes maintenance decision making still one step further by not only considering the current value of a deterioration parameter but also the future evolution, can also be reflected by the parameter t'. In the case study presented in Section 4.3, the maintenance action is always initiated at the point of detection by the CMS. However it could be economically more beneficial to initiate maintenance based on remaining useful life predictions and not on thresholds for condition monitored parameters (Camci 2009; Yang et al. 2008; Van Horenbeek and Pintelon 2013b). Incorporation of prognostic information on the component state (i.e. RUL) is subject of Chapter 6 (Van Horenbeek et al. 2012; Van Horenbeek and Pintelon 2013b), although it is already implicitly modeled by parameter t'.

4.2.4 Modeling secondary damage

The approach discussed in Section 4.2.3 also takes into account the effect of secondary damage. As this is potentially one of the most important parameters in quantifying the economic benefit of a CMS system, this should be modeled in a convenient way. Moreover, the performance of the CMS determines the capability of the system to prevent secondary damage. Threshold level $TH2$ determines the moment in the deterioration process from whereon the degradation of this component has an effect on the degradation process of other components. This threshold level is different for each specific component. A CMS with high efficiency (η) will be able to prevent secondary damage by detecting a potential failure in zone A or B of the P-F curve, which ensures a longer lifetime of the whole system while maintenance cost and downtime are reduced at the same time.

4.3 Case study

The added value of implementing a CMS in an onshore wind turbine gearbox (3MW), from the point of view of the gearbox manufacturer, is determined by using the modeling approach for the performance of the CMS as described in Section 4.2. The gearbox is commonly considered to be one of the most critical components in a wind turbine. It is responsible for around 15-20% of the maintenance costs and downtime (Garcia et al. 2006). The criticality of the gearbox in a wind turbine makes the gearbox one of the best candidates to be monitored by a CMS, since the CMS can potentially provide a large added value. An onshore application is considered in the case study, as all data available from the gearbox manufacturer handles gearboxes in onshore wind turbines (i.e. data on more than 800 onshore wind turbines over a time span of more than 8 years). Most of the data used for the case study is confidential and therefore no detailed numbers are given in the following sections, the results that are shown are multiplied with a certain scale factor in order to preserve confidentiality. More detailed descriptions on the parameters and data used to calculate the cost parameters for the considered case study can be found in

Bellens and Chemweno (2010). However, no details on the real data are given, the methodology and model applied to the case study are described rigorously and the results and conclusions from this study remain valid. Moreover, the proposed methodology remains valid even when other data are introduced into the model.

A comparison between two maintenance strategies is made to assess the economic value of a CMS. Strategy 1 is the gearbox manufacturer's current maintenance strategy and consists of a combination of time-based preventive maintenance and corrective maintenance. Maintenance strategy 2 considers the implementation of condition-based maintenance by introducing a CMS into the gearbox, which makes continuous monitoring of the gearbox possible. This comparison is made by developing a static, stochastic Monte Carlo simulation model for life cycle costing. The performance of the CMS and secondary damage modeling, as discussed in Section 4.2, will be applied to validate to which extend the CMS performance parameters are important when determining the economic benefit of a CMS.

Different steps to determine the added value of the implementation of a CMS in a wind turbine gearbox are followed. Firstly, the most important failure modes of the gearbox are selected by applying a cost-based failure mode and effect analysis (FMEA). Secondly, a reliability curve is fitted to the previously retained failure modes, which is used to model the failure behaviour in the simulation model. Finally, a life cycle cost structure is developed in order to determine the cost of both maintenance strategies. This makes it possible to determine the added value of the CMS implementation; moreover, the influence of the CMS performance parameters is determined by a sensitivity analysis.

4.3.1 Cost-based FMEA

FMEA is one of the well-known methods to determine the most critical failure modes of equipment, in this case the gearbox of the wind turbine. The risk priority number (RPN) (Arabian-Hoseynabadi et al. 2010) is probably the most widely used methodology to determine these critical failure modes. However, the method is also widely criticized for various reasons (Stamatis 2003); mainly because of the difficulty of assigning objective decision parameters. Because of this a cost-based FMEA (Rhee and Ishii 2003) methodology is applied to determine the critical failure modes of the gearbox. In the cost-based FMEA methodology, risk or criticality is measured in terms of estimated failure cost which is a product of probability of failure and the associated cost. The estimated cost is defined by the following equation:

$$Total\ estimated\ failure\ cost = \sum_{1}^{n} p_i \times c_i \tag{4.1}$$

Where p_i is the probability of occurrence of failure mode i, c_i is the associated cost with failure mode i and n is the total number of failure modes. In Equation 4.1, the probability of failure can be replaced with the actual number of field failures that occur within a specified period of time. The probability of occurrence of failure mode i and its associated cost are based on historical data of a gearbox population. The failure cost consists of labour cost, material cost and downtime cost. Expressing failure frequency and its severity in terms of cost is considered to be a better approach compared to RPN since cost is a measurable parameter that is easily understood and is associated with the severity of a failure. An additional advantage of the cost-based FMEA methodology is that the total estimated failure cost does not take ordinal values compared to the traditional RPN FMEA methodology. The failure cost for each failure mode over the entire gearbox population is given in Table 4.1.

Table 4.1: Total failure cost for all failure modes of a gearbox population. [Based on company database of gearbox population (Bellens and Chemweno 2010)]

	Failure mode	Failure cost (€)
1	High speed shaft bearing failure	10,207,393
2	Broken intermediate shaft	7,797,154
3	Intermediate shaft bearing failure	3,701,940
4	Planet bearing failure	3,515,432
5	Broken centre post	2,296,527
6	High speed shaft bearing black spot	1,999,723
7	Sun gear - broken teeth	1,951,066
8	Low speed shaft bearing failure	1,833,967
9	Intermediate shaft bearing failure	1,764,277
10	High speed shaft grinding temper failure	843,824
11	Broken low speed wheel	441,526
12	Oil pump failure	308,491
13	Intermediate shaft splash plate failure	90,858

Based on the cost-based FMEA a Pareto ranking of the most significant failure modes can be made. Pareto ranking of the 13 failure modes of the gearbox follows the 80%-20% rule, whereby 20% of the failures account for 80% of the total estimated failure cost. From Figure 4.4 it can be concluded that the first six failure modes account for 80% of the total estimated failure cost, and are therefore retained in the stochastic simulation model.

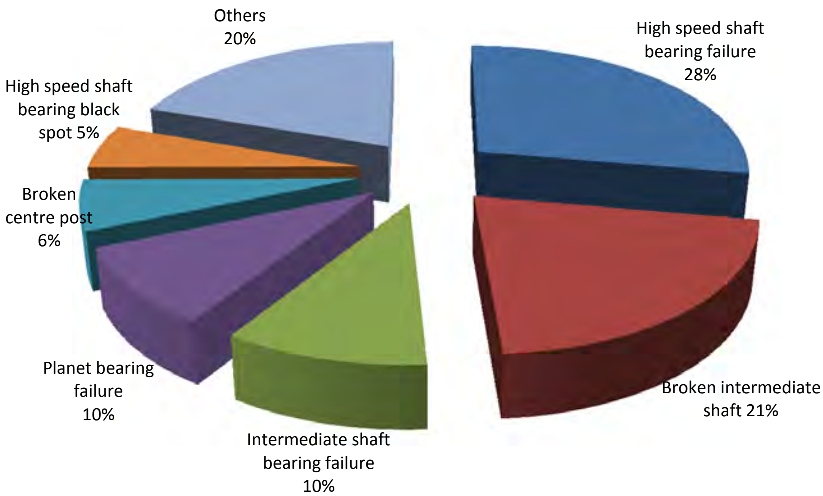

Figure 4.4: Cost distribution over the different failure modes for a wind turbine gearbox population.

4.3.2 Component reliability

To each of the six main failure modes, as determined by the cost-based FMEA methodology, a reliability curve is fitted. This is done by analyzing failure data of a population of gearboxes installed in onshore wind turbines for which information is closely recorded from commissioning to failure date. The purpose of analyzing the gearbox failure data is determining the failure distribution that fits best the dataset of each failure mode and deriving the corresponding parameters of these distributions. These are used to model the failure behavior of each failure mode. The failure distribution for each failure mode is a two parameter Weibull distribution with probability density function:

$$f(t) = \frac{\alpha}{\lambda^{\alpha}} t^{\alpha-1} e^{-\left(\frac{t}{\lambda}\right)^{\alpha}} \; ; \; for \; (t, \alpha, \lambda) > 0 \tag{4.2}$$

Where α is the shape parameter and λ is the scale parameter. The median rank method is used to rank the failure data and parameter estimation is based on maximum likelihood estimation. The α and λ parameter for each failure mode are displayed in Table 4.2 under the column 'Mode'. The columns 'LB' and 'UB' contain the values of respectively the lower and upper bound of the 90% confidence interval of the parameters' estimates.

Table 4.2: Weibull parameters for different failure modes.

	FM 1			FM 2			FM 3		
	LB	Mode	UB	LB	Mode	UB	LB	Mode	UB
α	0,8344	1,0038	1,1934	1,529	1,9897	2,5249	0,9971	1,4734	2,0696
$\lambda(h)$	1,97E+05	2,92E+05	4,83E+05	1.03E+05	1,44E+05	2,32E+05	1,84E+05	3,88E+05	1,35E+06

	FM 4			FM 5			FM 6		
	LB	Mode	UB	LB	Mode	UB	LB	Mode	UB
α	0,8492	1,4545	2,2728	0,4684	0,7927	1,2343	1,1696	2,7439	5,1304
$\lambda(h)$	2,04E+05	6,01E+05	5,27E+06	8,89E+05	6,31E+06	2,87E+08	9,07E+04	2,15E+05	2,85E+06

The obtained values for the Weibull parameters are estimates on the true values of the Weibull parameters of the entire gearbox population, which means there is uncertainty about the estimated reliability parameters. This is certainly the case because the data on the population of the gearboxes were highly censored, because a lot of gearboxes survived the study period. To make the deducted failure distributions more representative for the entire population of gearboxes, a 90% confidence interval on the Weibull parameters is considered in the stochastic simulation model.

4.3.3 Stochastic life cycle cost analysis (LCCA)

To quantify the benefit of implementing a CMS in a gearbox of an onshore wind turbine and determine the effect of the CMS performance on this added value, a stochastic life cycle cost analysis (LCCA) is performed. LCCA is an economic method for project evaluation in which all costs arising from design, production, operation, maintenance and eventually disposal of a product are considered to be potentially important to that decision (Asiedu 1998). Different maintenance strategies lead to a specific life cycle cost (LCC) because each strategy affects the gearbox maintenance in a different way (e.g. repair times, number of failures). The total life cycle cost of the wind turbine gearbox is calculated as:

$$LCC = C_{INV} + C_{SPP} + C_{CM} + C_{PM} + C_{PEN} + V_{REM} \tag{4.3}$$

Where C_{INV} the investment cost of the gearbox, C_{SPP} the cost for spare parts, C_{CM} the cost for corrective maintenance, C_{PM} the cost for preventive maintenance, C_{PEN} the cost for claimed penalties and V_{REM} the revenue for the remaining value of the gearbox. These costs are discounted to their present value according to the method described further on in Section 4.3.3. The total life cycle cost is calculated from the viewpoint of the gearbox manufacturer. Each of these cost elements are located at the highest level of the LCC structure and branches further into lower level cost elements, resulting in a LCC tree.

Investment cost

The investment cost for the gearbox is incurred only once at the beginning of the life cycle. The cost contains a share of the engineering and part manufacturing cost. Mark that the investment cost for a CMS (strategy 2) is not part of this cost element but is considered in the preventive maintenance cost (C_{PM}).

Spare parts cost (C_{SPP})

The spare parts cost is composed of ordering and holding costs:

$$C_{SPP} = C_{SPP\,ord} + C_{SPP\,hold\,comp} + C_{SPP\,hold\,GB} \tag{4.4}$$

Where $C_{SPP\,ord}$ is the order cost for spare parts and is incurred at each repair action that includes component or gearbox replacement. It includes a setup cost and a material cost for FM_i or a complete gearbox. $C_{SPP\,hold\,comp}$ is the holding cost for component spare parts and $C_{SPP\,hold\,GB}$ is the holding cost for spare gearboxes. The holding cost is determined by a percentage for cost of capital, a percentage for insurance and taxes and a percentage for the use of storage space.

Corrective maintenance cost (C_{CM})

Component failures are determined based on the method described into more detail in Sections 4.3.4 - 4.3.6. The corrective maintenance costs are composed of the cost for diagnostic actions, cost for repair actions and the material cost for tools and equipment for these actions. The purpose of a diagnostic action is twofold: confirming that the turbine failure is caused by the gearbox and consequentially determining the failure mode of the gearbox. The diagnostic action is followed by a repair action from the moment that spare parts are available. For maintenance strategy 2 only the costs for zone F repairs are considered as CM, repairs and thus costs for zones A, B and C are considered as CBM.

$$\begin{aligned} C_{CM} = {} & C_{CM\,diag\,tr} + C_{CM\,diag\,la} + C_{CM\,rep\,tr} + C_{CM\,rep\,la} \\ & + C_{CM\,rep\,ac} + C_{CM\,tool\,diag} + C_{CM\,tool\,rep} \end{aligned} \tag{4.5}$$

Where $C_{CM\,diag\,tr}$ is the travel cost for an onsite diagnostic action that consists of the technician's wage and vehicle costs. $C_{CM\,diag\,la}$ is the labour cost for an onsite diagnostic action which depends on the failure mode specific time-to-diagnose. $C_{CM\,rep\,tr}$ is the travel cost for onsite repair actions and $C_{CM\,rep\,la}$ is the labor cost for a repair action. Depending on the two parameters for consequential damage (Section 4.2.4) and company workshop repair, different corrective repair actions are possible (e.g. onsite repair, workshop repair (Table 4.3)). $C_{CM\,rep\,ac}$ is the access cost for a repair action and includes crane hiring and transportation costs. Finally, $C_{CM\,tool\,diag}$ and $C_{CM\,tool\,rep}$ are respectively the cost for diagnostic and repair tools.

Preventive maintenance cost (C_{PM})

The preventive maintenance costs are composed of the cost for 'consumables', the cost for condition-based maintenance (CBM) and the cost for time-based maintenance (TBM). The cost for consumables includes the costs for the materials that are used during a TBM inspection and during an oil change. The cost for CBM includes the costs for a CMS, false alarms, diagnostic actions and repair actions. Similar to the corrective repair actions, a repair action triggered by a CMS is always preceded by an onsite diagnostic action to confirm the diagnosis of the CMS. For maintenance strategy 2 failures which are detected by the CMS before point F on the PF-curve are charged as costs for CBM. Failures which are not detected before point F evolve into functional failures and are charged as costs for CM. The cost for TBM contains the costs for preventive inspections, oil changes and related tools.

$$\begin{aligned} C_{PM} = {} & C_{PM\,cons\,ord} + C_{PM\,cons\,hold} + C_{PM\,oil\,ord} + C_{CBM\,CMS\,op\,ext} \\ & + C_{CBM\,CMS\,inv} + C_{CBM\,false\,alarms\,tr} + C_{C\,CBM\,false\,alarms\,la} \\ & + C_{CBM\,diag\,tr} + C_{CBM\,diag\,la} + C_{CBM\,rep\,tr} + C_{CBM\,rep\,la} \\ & + C_{CBM\,rep\,ac} + C_{TBM\,insp\,tr} + C_{TBM\,insp\,la} + C_{TBM\,oil\,tr} \\ & + C_{TBM\,oil\,la} + C_{TBM\,oil\,ac} + C_{TBM\,tool\,insp} \end{aligned} \tag{4.6}$$

Where $C_{PM\,cons\,ord}$ is the ordering cost for consumables used during a TBM inspection. It includes a setup cost and a TBM material cost. $C_{PM\,cons\,hold}$ is the holding cost for TBM consumables. $C_{PM\,oil\,ord}$ is the ordering cost for oil and is incurred periodically at each oil change. The time interval for oil changes is 2 years. $C_{CBM\,CMS\,op\,ext}$ is the CMS operating cost, which includes failure reporting, software updates and maintenance of the CMS. $C_{CBM\,CMS\,inv}$ is the investment cost for the CMS, which includes the material (e.g. sensors, controller and communication processor), installation and setup or commissioning cost. $C_{CBM\,false\,alarms\,tr}$ and $C_{CBM\,false\,alarms\,la}$ are the travel and labor cost for false alarms. False alarms are modeled by a fixed number per year and can be considered as a diagnostic action triggered by a false indication of the CMS. $C_{CBM\,diag\,tr}$ is the travel cost and $C_{CBM\,diag\,la}$ is the labor cost for an onsite diagnosis based on condition monitoring information. $C_{CBM\,rep\,tr}$ is the travel cost and $C_{CBM\,rep\,la}$ is the labor cost for an onsite repair action based on condition monitoring information. $C_{CBM\,rep\,ac}$ is the access cost for a repair action based on condition monitoring information and includes the cost for crane hiring and transportation of spare parts from the parts pool to the wind turbine. $C_{TBM\,insp\,tr}$, $C_{TBM\,insp\,la}$, $C_{TBM\,oil\,tr}$ and $C_{TBM\,oil\,la}$ are the travel and labor cost for respectively a TBM inspection and a preventive oil change. $C_{TBM\ oil\ ac}$ is the access cost, determined by the rental cost for an oil flush unit, for a preventive oil change. $C_{TBM\ tool\ insp}$ is the cost for tools used for a TBM inspection.

Penalty cost (C_{PEN})

The penalty cost is the cost that is charged by the wind turbine operator for downtime caused by a gearbox failure. The penalty cost is a constant cost rate per hour of downtime. The weather conditions during the downtime do not influence the penalty rate and the charged downtime cost is not reduced when weather conditions do not allow operation of the wind turbine. When a turbine is down a diagnostic action is performed first. This time is not included into the charged downtime. When it is clear that the failure of the turbine is caused by the gearbox and on which failure mode it failed, the charged downtime starts running.

Revenue for remaining value (V_{REM})

The residual value of a gearbox which has operated for a period as long as its design lifetime equals its scrap value. A gearbox which has not reached its design lifetime upon failure is used as spare part for similar wind turbines after repair at the gearbox manufacturing company. When the gearbox is completely lost due to failure and no repair is possible, the remaining value equals the scrap value of the gearbox.

Discounted cash flows

All cash flows that are calculated, using the LCC structure as discussed in the previous sections, are discounted to their present value by using the following formula:

$$LCC = \sum_{j=0}^{20} \frac{C_j}{(1+d)^j} \tag{4.7}$$

An LCC period of 20 years, which is the design lifetime of a gearbox, is used; where d is the discount rate and C_j is the net cash flow in year j. A discount rate of 10% is used in this case study, which equals the Weighted Average Cost of Capital (WACC) of the gearbox manufacturer.

4.3.4 Linking maintenance actions to the deterioration process

The nature of the maintenance actions on the wind turbine gearbox depends on two major factors, the accessibility of the failed component in the gearbox and the possible consequential damage that occurs if the deterioration process has evolved too far. In the stochastic model these properties are indicated by two Boolean parameters $B_{i\,company\,workshop}$ and $B_{i\,consequential\,damage}$ for each failure mode FM_i. $B_{i\,company\,workshop}$ is set to 'true' when the failure mode requires a gearbox dismount for having parts replaced at the company workshop. The parameter is set to 'false' when the parts related to the failure mode can be replaced on site. $B_{i\,consequential\,damage}$ is set to 'true' when a failure on FM_i in zone C or F causes consequential damage, otherwise the parameter is set to 'false'. The values for these two parameters for the different failure modes are listed in Table 4.3. When a failure mode evolves into zone C or F and consequential damage is possible, the gearbox is completely deteriorated.

Table 4.3: Overview of boolean parameters determined by the component's accessibility and consequential damage propagation.

Failure modes	Accessibility	Deterioration
	$B_{i\,company\,workshop}$	$B_{i\,consequential\,damage}$
FM 1	0	0
FM 2	0	1
FM 3	1	1
FM 4	1	0
FM 5	1	1
FM 6	0	1

When the concept on the deterioration process, presented in Section 4.2, is combined with the maintenance actions parameters of Table 4.3, the flow chart as shown in Figure 4.5 is obtained. When studying this chart, it should be kept in mind that each failure mode has its own set of threshold values ($TH1_i$ and $TH2_i$) and corresponding P-F curve, and that a CMS has a set of performance parameters (γ_i,η_i) for each of the six failure modes. Consider a CMS that has, as far as FM_1 concerns, the ability to detect 90% of the failures on FM_1 ($\gamma_1 = 90\%$), but detects them in a very late stage $t' = 5\%$ ($\eta_1 = 5\%$). From experience, the company knows that for FM_1 a failure causes limited damage until $t' = 85\%$ ($TH1_1 = 85\%$) and that maximum component damage starts from $t' = 25\%$ ($TH2_1 = 25\%$). Disregarding the cause, a failure on FM_1 starts to develop at a certain point in time (point P). The CMS detects the failure with probability $\gamma_1 = 90\%$. Let us assume that the CMS detects this failure. The failure evolves through zone A, but is not detected here since $TH1_1 > \eta_1$. The failure evolves through zone B but is not detected here either since $TH2_1 > \eta_1$. The failure evolves through zone C and is detected in zone C since $TH2_1 > \eta_1 > 0$. In this zone the part or subassembly related to FM_1 has deteriorated to maximum component damage. Based on Table 4.3, a failure on FM_1 does not cause consequential damage and can be repaired on site. According to the flow chart (Figure 4.5) this results in a repair action in which the failed component or subassembly is replaced on site.

It is possible to determine for each failure on FM_i an appropriate maintenance action based on the following inputs:

- CMS performance parameters γ_i and η_i for each failure mode FM_i
- threshold values $TH1_i$ and $TH2_i$ for each failure mode FM_i
- requirements on gearbox dismount and consequential damage (Table 4.3)
- maintenance flowchart (Figure 4.5)

Note that the concept of dividing the P-F curve for each failure mode into four failure zones is only relevant when applying maintenance strategy 2. For each maintenance action an extensive cost calculation is made by using Monte Carlo simulation.

4.3.5 Modeling added value of the CMS

The most important benefit of implementing a CMS lies in the ability to detect a potential failure before the actual functional failure happens, which reduces or completely prevents consequential damage and corrective maintenance actions. Preventing consequential damage ensures a reduction in cost and a gain in availability of the equipment. Although preventing consequential damage is an important or maybe the most important gain when implementing a CMS, the CMS adds value in other areas of maintenance too. These effects are modeled in this chapter by introducing a set of β-parameters. These parameters describe the effect of a CMS on different life cycle cost elements.

Effect on diagnosis time - β_{1i}

When a failure is detected by a CMS less time is needed to point out the relevant failure mode, which results in a reduction of the time-to-diagnose. This effect is noticeable for maintenance strategy 2 in case of detection of the failure in zone A, B or C. The effect is modeled by parameter β_{1i} and is specific for each failure mode:

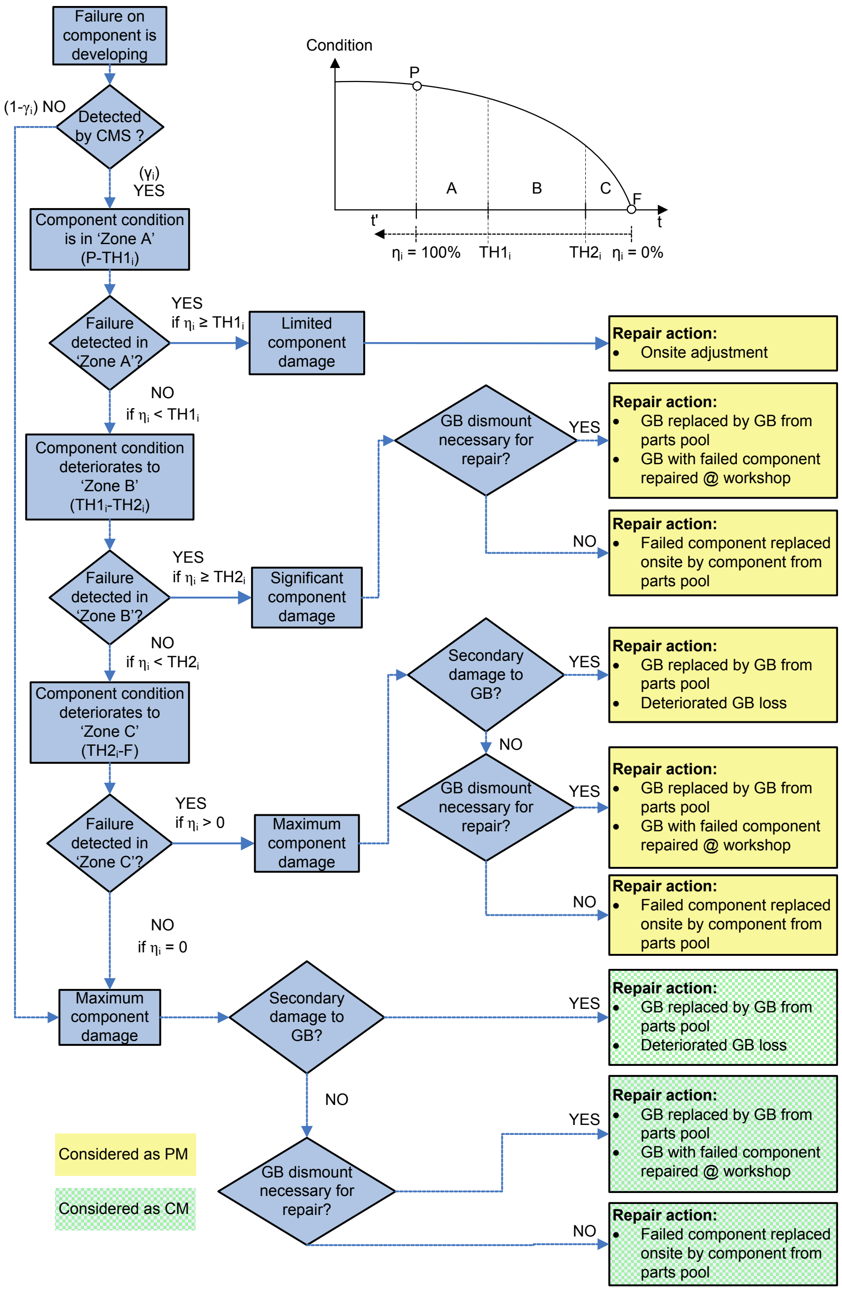

Figure 4.5: Flow chart for determining the appropriate repair action.

$$\beta_{1i} = \frac{TTD_{i2}}{TTD_{i1}} \tag{4.8}$$

TTD_{i1} is the time-to-diagnose for a failure on FM_i in maintenance strategy 1 and TTD_{i2} is the time-to-diagnose for a failure on FM_i in maintenance strategy 2.

Effect on spare parts stock level - β_{2i}

A failure that is detected by the CMS before evolving into a functional failure creates the opportunity to keep the gearbox running while the lead time of the appropriate components is passing by. As a result the stock level can be reduced without increasing the risk for running out of spare parts. This effect is modeled by parameter β_{2i}:

$$\beta_{2i} = \frac{K_{i2\,CM_{spp\ stock}}}{K_{i1\,CM_{spp\ stock}}} \tag{4.9}$$

$K_{i1\,CM\ spp\ stock}$ is the stock level of spare parts for failure mode FM_i in strategy 1 and $K_{i2\,CM\ spp\ stock}$ is the stock level of spare parts for failure mode FM_i in strategy 2.

Effect on TBM interval - β_{3i}

When a CMS is available the TBM interval can be extended because unnecessary preventive inspections can be excluded based on the condition readings of the CMS. This effect is modeled by parameter β_{3i}:

$$\beta_{3i} = \frac{T_{2\,TBM\ interval}}{T_{1\,TBM\ interval}} \tag{4.10}$$

$T_{1\,TBM\ interval}$ is the time between two successive inspections in strategy 1 and $T_{2\,TBM\ interval}$ is the time between two successive inspections in strategy 2.

Effect on repair time - β_{4i}

The model which divides the P-F curve of each failure mode into four zones creates the opportunity to have different repair actions for the same failure mode. This repair action is depending on the spot of the P-F curve where the evolving failure is detected, as illustrated in Section 4.2. When a CMS is available certain repair actions can be prevented or at least shortened. This effect is modeled by parameter β_{4i}:

$$\beta_{4i} = \frac{TTR_{i2z}}{TTR_{i1}} \tag{4.11}$$

TTR_{i1} is the time to repair a failure on failure mode FM_i in strategy 1 and TTR_{i2z} is the time to repair a failure on failure mode FM_i in strategy 2 when the failure is detected in zone z, where z equals A, B, C or F.

4.3.6 Simulation model structure

The stochastic Monte Carlo simulation model combines the concept of the P-F curve with the description of cost calculations and cash flows from the previous sections. The model structure is composed of multiple steps which are repeated for each iteration of a simulation run. Each iteration results in a life cycle cost for maintenance strategy 1 and maintenance strategy 2. The model structure is depicted in Figure 4.6 and the different steps are described in the following paragraphs.

Step 1: The distribution parameters (α_i, λ_i) and the accompanying lower and upper bounds of the 90% confidence interval are known for each failure mode FM_i (Section 4.3.2). In this step, for each failure mode FM_i, a set of distribution parameters (α_i, λ_i) is determined by taking a Monte Carlo sample from the triangular distributions for the α- and λ-parameter defined in Table 4.2. These values characterize this Monte Carlo iteration and remain unchanged during this iteration. The time-to-failure for each failure mode FM_i is now defined by the Weibull distribution with parameters (α_i, λ_i).

Step 2: For each failure mode FM_i failure times are taken repeatedly from the corresponding Weibull (α_i, λ_i) reliability distribution in order to determine point F of the P-F curve. Point P of the P-F curve can be determined by measurable criteria (e.g. vibration measurements, oil analysis) or expert knowledge on the degradation process. Christer and Waller (1984) prove that it is possible to obtain a subjective estimate of the probability density function of the delay time (i.e. time between P and F). The number of failures occurring in the same year j are counted for each year of the LCC period and for each failure mode FM_i.

Step 3: For each input parameter that is defined by a distribution and is common for all failure modes (e.g. travel cost for onsite diagnostic action), a Monte Carlo sample is taken. These values are proper to this iteration and remain unchanged during this iteration. A detailed description on these parameters and the way their variability is modeled can be found in (Bellens and Chemweno 2010).

Step 4: The values for the parameters that are proper to each failure mode (e.g. TTR, material cost) and are used in the cost calculations are sampled from their respective distributions. These values are proper to this iteration and remain unchanged during this iteration. A detailed description on these parameters and the way their variability is modeled can be found in (Bellens and Chemweno 2010).

Step 5: For maintenance strategy 2, the failures on failure mode FM_i occurring in each year j are separated into categories depending on the CMS performance (γ_i, η_i) and the threshold values $TH1_i$ and $TH2_i$ for that failure mode. The category k is determined by the zone on the P-F curve where the failure is detected (zone A, B, C or F).

Step 6a and 6b: This step is a preparatory step for the actual LCC calculation in Step 7 and is based on the LCC tree for both maintenance strategies. The step calculates the cost of each lowest level element of the tree for each failure mode FM_i, regardless whether this cost (event) will actually occur during the life cycle of the gearbox in this iteration (e.g. the holding cost for keeping spare parts for FM_1 for one year, the cost for one TBM inspection, the labor cost for one CM repair action on FM_1). The input parameters and the parameters corresponding to each failure mode determined in Step 3 and Step 4 respectively are used for these calculations.

Step 7a and 7b: Based on the number of events (repairs on FM_i, diagnoses, inspections, oil changes, etc.) occurring in year j and the costs for each cost element (Step 6a and 6b) a cash flow is calculated for both maintenance strategies. The net cash flow in year j is the sum of the cash flows for each failure mode FM_i in that year. All cash flows are discounted to their present value.

Step 8a and 8b: Summing all discounted cash flows results in the LCC for both maintenance strategies for this iteration.

The resulting life cycle cost for both maintenance strategies is based on the same failure behavior in the stochastic simulation model. This stresses the given that the differentiation in life cycle cost is merely caused by the way the gearbox is maintained. It can be thought of as two identical gearboxes installed in an identical working environment but maintained according to a different maintenance strategy.

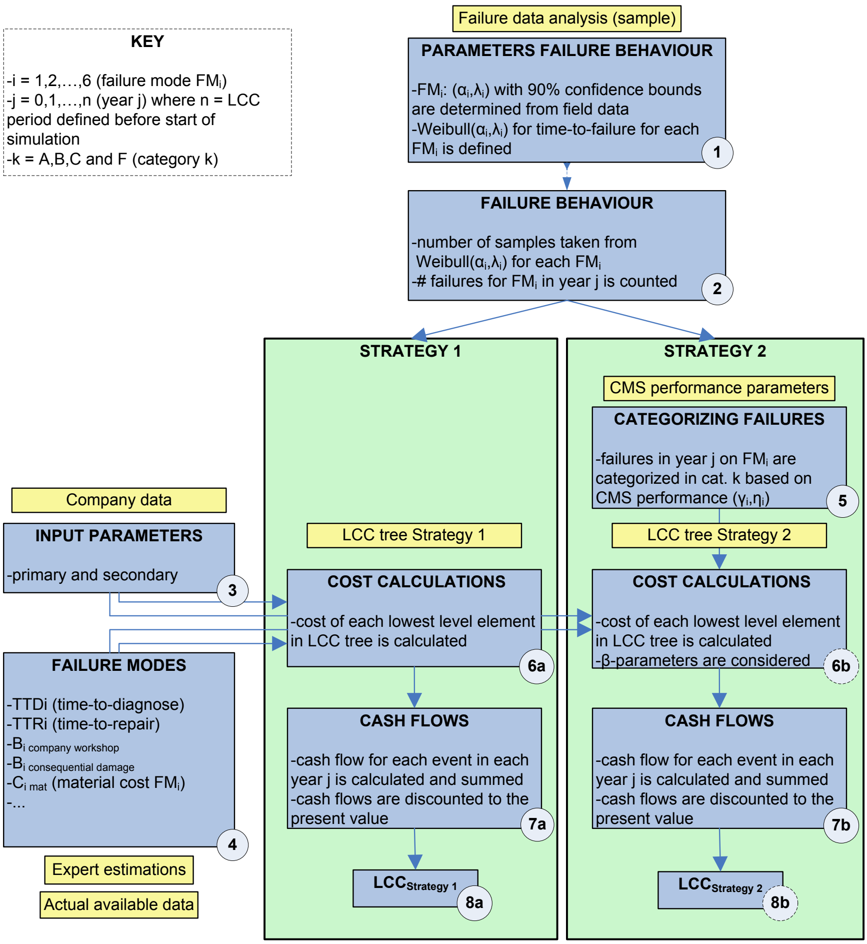

Figure 4.6: Stochastic simulation model structure.

4.3.7 CMS system

The CMS used in this study is an oil analysis system based on particle counting combined with a vibration measurement system. The detectability (γ_i) and efficiency (η_i) parameters for this combined system are summarized in Table 4.4 for each failure mode FM_i. These parameters are estimated based on expert knowledge and thorough investigations of the CMS provider. Failure modes which are not detectable by the CMS (i.e. $\gamma_i = 0$) are maintained as in the current maintenance strategy (i.e. time-based preventive or corrective maintenance).

Table 4.4: CMS parameters.

CMS type	Oil analysis + Vibration measurement	
$C_{CBM\,CMS\,inv}$ (min-mode-max) (€)	18750 - 22000 - 25250	
$C_{CBM\,CMS\,op\,ext}$ (min-mode-max) (€/y)	1700 - 2100 - 2500	
Performance	**Detectability** (γ_i) (%)	**Efficiency** (η_i) (%)
FM1	100	95
FM2	70	95
FM3	0	0
FM4	100	80
FM5	0	0
FM6	100	80

4.4 Results

First a base simulation has been performed, where the model was fed with parameters as close as possible to the company's current working method. The life-cycle cost and downtime distribution of both maintenance strategies for a gearbox of an onshore wind turbine were compared. Finally, a sensitivity analysis of the output on the detectability and efficiency parameters, which model the performance of the CMS, was performed. All simulations consisted of 3000 Monte Carlo iterations, which yields sufficiently accurate results (Vose 2008).

4.4.1 Base simulation LCC results

The base simulation is the simulation that is run with the parameter values that were collected or estimated during the study. This simulation is the most representative for the company's current environment and actual working method. The statistical results for the base simulation of the life-cycle cost for both maintenance strategies for a gearbox in an onshore wind turbine are summarized in Table 4.5. The corresponding histogram plots for both maintenance strategies are depicted in Figure 4.7. The mean expected life-cycle cost of maintenance strategy 1 (€775018) is higher than the life-cycle cost of maintenance strategy 2 (€728904), which indicates that the CMS (Section 4.3.7) adds value (€46114) to the maintenance strategy of the company. Moreover, Figure 4.7 clearly shows that the spread of the LCC values is smaller for strategy 2 than for strategy 1. Maintenance strategy 2 contains less variability and therefore represents a lower risk for extreme values of the LCC compared to maintenance strategy 1. This is confirmed by the smaller standard deviation for strategy 2 as shown in Table 4.5. The reason for the lower variability in LCC for maintenance strategy 2 is that for particular failure modes the CMS prevents failures from evolving into zone C or a functional failure (point F). The cost of these failures can be very high if due to consequential damage an entire gearbox needs to be replaced. Avoiding this consequential damage reduces the cases with the highest LCC and thus reduces the variability. This is in line with earlier conducted studies as mentioned in (Nielsen and Sørensen 2011).

Table 4.5: Statistical results of the LCC simulation for maintenance strategy 1 and maintenance strategy 2 of a gearbox in an onshore wind turbine (for reasons of confidentiality, a scale factor is applied).

Statistics	$LCC_{Strategy\,1}$ (€)	$LCC_{Strategy\,2}$ (€)
Mean	775 018	728 904
Stand. dev.	111 241	75 643
10th percentile	654 686	665 091
50th percentile	747 793	691 574
90th percentile	918 663	833 666

The averages of the different cost elements that add up to the total life-cycle cost of both maintenance strategies are shown in Figure 4.8. Maintenance strategy 2 has a lower cost for corrective maintenance, but a higher cost for preventive maintenance compared to maintenance strategy 1. More preventive maintenance actions, based on condition monitoring readings, are performed in maintenance strategy 2, but on the other hand this results in less corrective maintenance actions. When the costs for CM and PM are added for both maintenance strategies, the implementation of a CMS results in an average cost

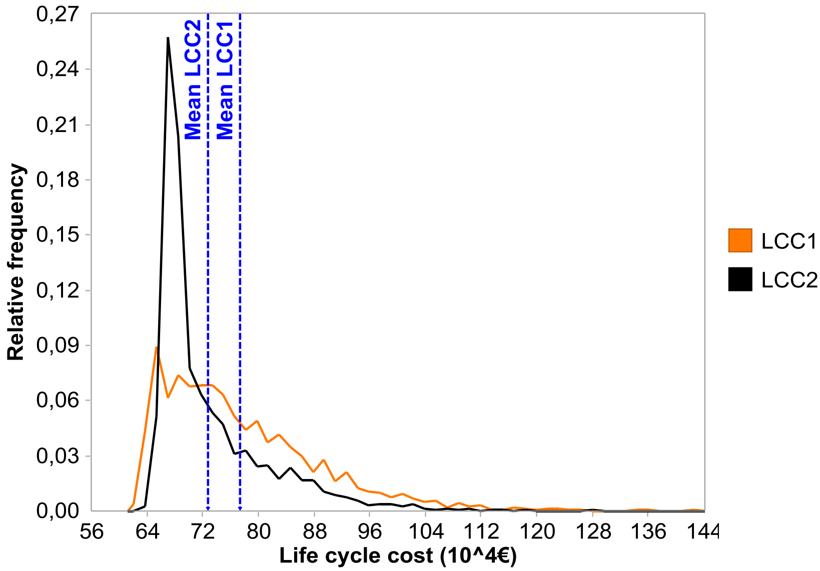

Figure 4.7: Histogram plots of the LCC for maintenance strategy 1 (LCC1) and maintenance strategy 2 (LCC2).

reduction of €6138. Compared to the reduction in spare parts cost (€47114) it indicates that the added value of the CMS lies more in secondary effects, like the reduction of spare part costs due to prevention of consequential damage.

4.4.2 Base simulation downtime results

The average availability of the gearbox in an onshore wind turbine for maintenance strategy 1 is $99.55 \pm 0.00107\%$; while the availability when applying maintenance strategy 2 is $99.73 \pm 0.00078\%$. The difference between both maintenance strategies can be explained by a potential shorter repair time due to prevention of degradation accumulation when implementing a CMS. Figure 4.9 illustrates the histogram plot of total downtime for the gearbox in an onshore wind turbine for both maintenance strategies.

4.4.3 Added value of the CMS

The added value of integrating a CMS in the maintenance strategy can be calculated by subtracting the values of the LCC of both maintenance strategies

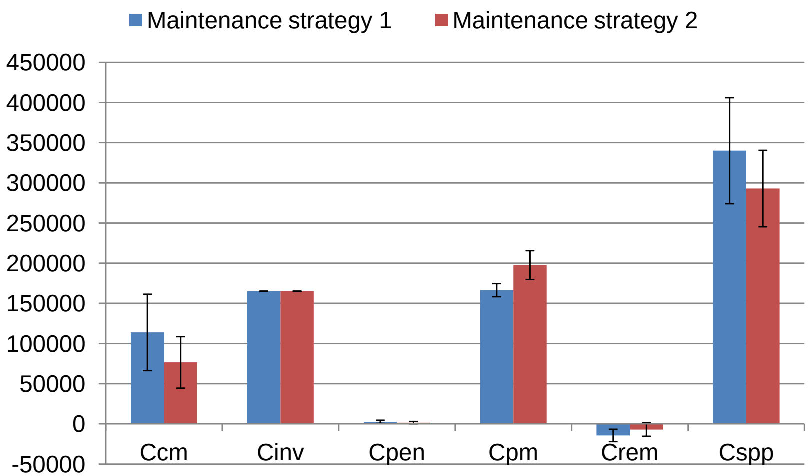

Figure 4.8: Cost breakdown for both maintenance strategies, the averages and standard deviation for all costs are depicted.

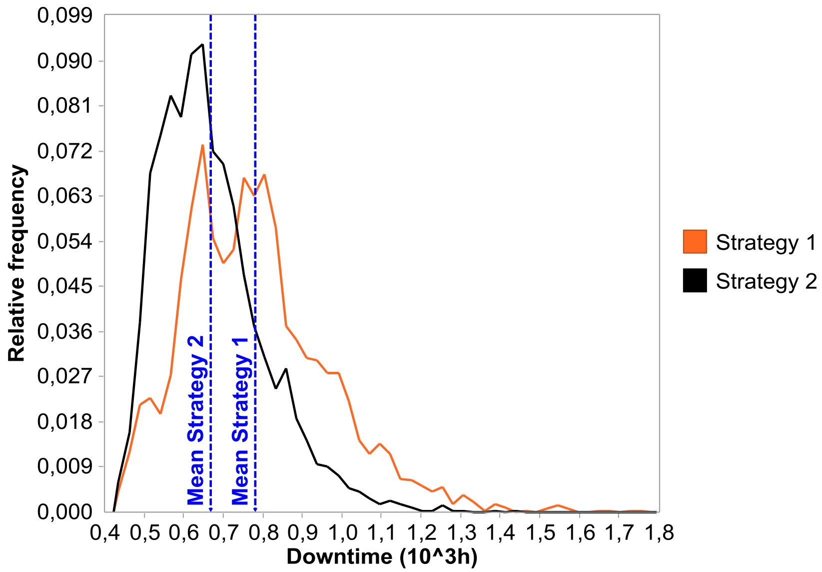

Figure 4.9: Histogram plot of the total downtime for both maintenance strategies.

for each simulation. This results in a mean added value of €46114 when a CMS is integrated in a gearbox of an onshore wind turbine. However, caution must be paid when drawing conclusions about the frequency of the cases in which strategy 2 results in a lower LCC than strategy 1. It is important to consider the difference in LCC between strategy 1 and 2 ($\Delta LCC_{Strategy\,1-Strategy\,2}$) for each and the same iteration. The added value is calculated by subtracting the LCC of strategy 2 from the LCC of strategy 1. This results in Figure 4.10 where 59.65% of the cases have $\Delta LCC_{Strategy\,1-Strategy\,2} \geq 0$. Where ($\Delta LCC_{Strategy\,1-Strategy\,2}$) is positive, the integration of a CMS in the maintenance strategy is justified. Thus for onshore applications the integration of CMS in the maintenance strategy for a gearbox is justified for 59.65% of the cases.

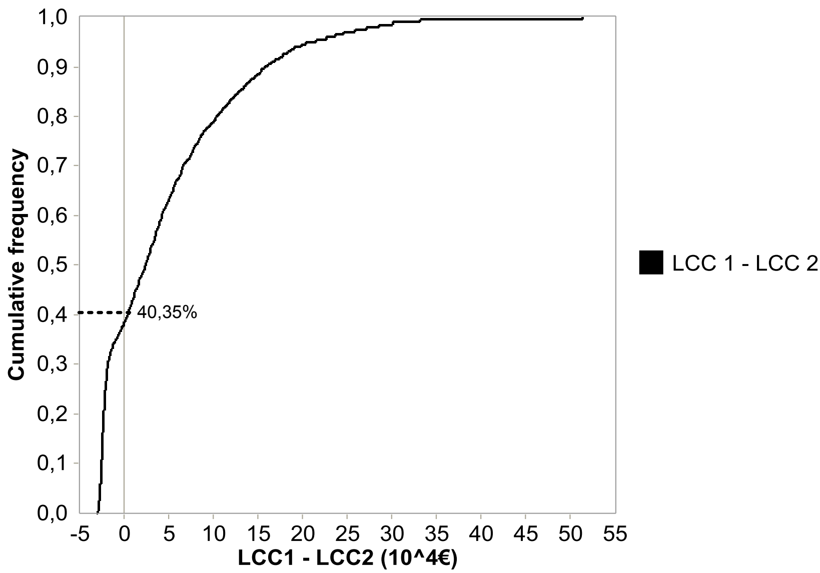

Figure 4.10: Cumulative frequency plot of ($\Delta LCC_{Strategy\,1-Strategy\,2}$) for a gearbox in an onshore wind turbine.

4.4.4 CMS performance

Figure 4.11 illustrates the effect of the two CMS performance parameters γ_i (detectability) and η_i (efficiency) on the added value of integrating a CMS in the maintenance strategy. The effect of γ_i is investigated while keeping η_i at the default values as defined in Table 4.4. No distinction is made in CMS detectability between the failure modes ($\gamma_i = \gamma_1 = \ldots = \gamma_6$). The effect of η_i

is investigated while keeping γ_i at the default values as defined in Table 4.4 for all failure modes. No distinction is made in CMS efficiency between the failure modes ($\eta_i = \eta_1 = \ldots = \eta_6$). At all times the threshold values $TH1_i$ and $TH2_i$ are kept constant at respectively 90% and 15%. The mean added value of strategy 2 over strategy 1 increases linearly with γ_i. Integrating a CMS to the maintenance strategy starts generating added value when the CMS reaches a detectability $\gamma_i = 19.5\%$ for each failure mode. The mean added value of strategy 2 reaches a maximum of €95306 when $\gamma_i = 100\%$. The mean added value of strategy 2 over strategy 1 shows a discontinuous function when varying η_i. The discontinuous character is caused by the threshold values $TH1_i$ and $TH2_i$ which are preset at 90% and 15%. The created levels in the graph show, from right to left, zone A, zone B, zone C and point F. For the values of $\eta_i < 15\%$ (detection in zone C or point F), implementation of a CMS into a gearbox of an onshore wind turbine is not justified.

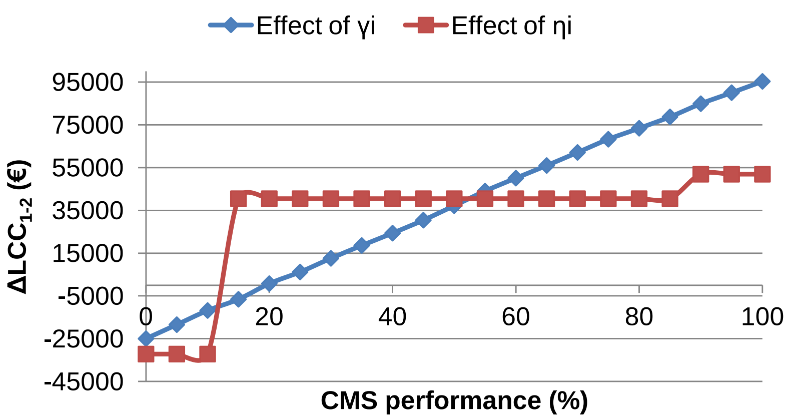

Figure 4.11: Effect of γ_i and η_i on mean ($\Delta LCC_{Strategy\,1-Strategy\,2}$).

The mean economic added value of the perfect CMS would be €99844. This sensitivity analysis on the parameters γ_i and η_i of the CMS clearly demonstrates that it is crucial to take the CMS performance into account when determining the economic added value. Entirely different conclusions about the economic benefit are drawn when the performance of the CMS is not perfect.

4.4.5 Effect of false alarms

In reality the number of false alarms depends on how strict the alarm levels for the CMS are preset. The stricter the alarm levels of the CMS are set; the more false alarms can be expected. But on the other hand the probability of missing out on a failure is reduced. Figure 4.12 illustrates the effect of the number of false alarms per year on the added value of maintenance strategy 2 over strategy 1. The other parameters in the model are kept at the values as in the base simulation. The results show that no more than 5 false alarms per year should occur in order to maintain the positive value of implementing a CMS.

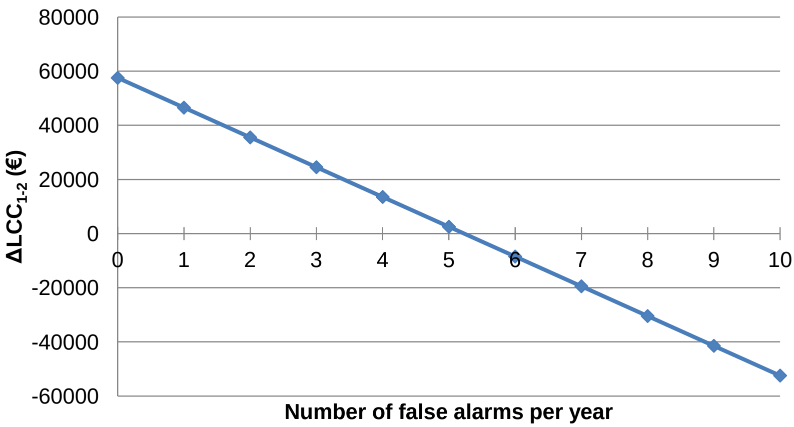

Figure 4.12: Effect of false alarms per year on mean $(\Delta LCC_{Strategy\ 1-Strategy\ 2})$.

4.4.6 Discussion

As the results show it is of major importance to take into account the performance of a CMS when quantifying the economic value of its implementation into a gearbox of an onshore wind turbine. The proposed methodology allows to include the performance of a CMS and potential development of consequential damage into the decision making process on the implementation of a CMS, which is the major contribution of this research. The presented model can be extended in several ways. First, the performance of the CMS can be optimized while making a trade-off with the cost of the CMS, as it can be expected that when the performance of the CMS increases, the cost will also increase. Secondly, the inclusion of uncertainty on the defined zones on the P-F curve would be an interesting extension of the current model, as it is assumed in the current model that the measured degradation zone perfectly matches with the real degradation zone. Thirdly, the described methodology can be extended with the inclusion of the real degradation processes and condition monitoring information, which can be used to model the P-F curve, when available. Moreover, the case study can be extended when the entire relation between efficiency η and detectability γ is known. Finally, incorporation of prognostic information (i.e. RUL) about the component state can be subject of further research, although it is already implicitly modeled by parameter t'. The last two points are discussed in Chapters 5 and 6.

Possibilities for future development by extending the scope of the problem are: (i) the inclusion of inventory management into the model, (ii) application to offshore wind turbines and (iii) application to an entire wind farm rather than a single wind turbine. The results show a major reduction in spare parts and inventory costs when a CMS is implemented. A more detailed investigation on these inventory costs can even further increase the economic value of a CMS. This makes joint optimization of the maintenance and inventory policy an interesting subject that is further studied in Chapter 7 of this thesis. This chapter discusses the application of an onshore wind turbine, it is expected that the implementation of a CMS in an offshore wind turbine would even generate more value due to the larger dependence on weather conditions, the difficult accessibility and the severe operating environment. Moreover, the extension to multiple wind turbines or even an entire wind farm would lead to new insights on maintenance management for wind turbines, as for that case a multi-system approach with dependencies between wind turbines and corresponding maintenance opportunities should be taken into account to schedule maintenance actions (Van Horenbeek et al. 2012; Bedford et al. 2011; Van Horenbeek, Pintelon, and Muchiri 2010). The model presented further on in Chapter 6 is applicable to these type of problems (Van Horenbeek and Pintelon 2013b). When considering an entire wind farm, it is expected that the added value of implementation of a CMS will even further increase, as maintenance on multiple wind turbines can be combined (Van Horenbeek et al. 2012). An initial study for multiple wind turbines based on the model discussed in Chapter 6 of this dissertation is presented in Van Horenbeek et al. (2012).

Furthermore, it is interesting to note that the presented model determines the economic value of a CMS and the corresponding decision to implement or not, but it does not generate an optimal maintenance plan based on condition monitoring information. The scope of the model is limited to assist decision makers in a long-term investment decision. So when the decision is made to implement a CMS because it generates value for a company, other models are necessary to make dynamic real-time decisions based on the condition monitoring and corresponding predictive information on component degradation and health state. These type of models are the subject of Chapter 5 and 6.

4.5 Conclusions

A new approach to modeling the performance or effectiveness of a CMS and secondary or consequential damage accumulation is presented in this chapter. The methodology is illustrated by an extensive case study on a wind turbine gearbox. The expected life cycle cost of two maintenance strategies is determined and compared by a stochastic simulation model. This case study shows the added value of implementing a CMS into the gearbox compared to the currently applied maintenance strategy. Furthermore, the sensitivity analysis indicates that the performance of the CMS has a major influence on the generated added value. The study proves that the performance of a CMS should be taken into account in order to draw the right conclusions on the real economic value.

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Chapter 5

Prognostics for real-time optimal maintenance

When the decision to invest in condition monitoring technology is made and the right equipment is installed, one of course needs models to schedule maintenance in an optimal and dynamic way. The decision models presented in this chapter specifically address this type of problem by scheduling maintenance activities based on the gathered condition monitoring data and corresponding predictive information. Hence, predictive maintenance models for real-time maintenance decision making are presented. The models are specifically applied to three industrial case studies in order to show their applicability in real-life maintenance problems. First, two case studies are presented where a maintenance cost versus product quality optimization is performed based on condition monitoring information. Secondly, a case study on production capacity optimization using temperature condition monitoring is presented. This last case study shows the wider applicability of the developed models as it is illustrated that condition monitoring information is not only valuable for maintenance purposes, but also for production capacity optimization. Note that both product quality and production capacity are considered as maintenance objectives, as such extending

This chapter is based on A. Van Horenbeek, A. Bey-Temsamani, et al. (2011). "Prognostics for optimal maintenance: maintenance cost versus product quality optimization for industrial cases". In: *Proceedings of the 6th world congress on engineering asset management* and A. Bey-Temsamani, A. Van Horenbeek, et al. (2013). "Prognostics for optimal maintenance: industrial production capacity optimization using temperature condition monitoring". In: *Proceedings of the 26th International Congress on Condition Monitoring and Diagnostics Engineering Management (COMADEM)* the scope of the commonly available maintenance optimization models (see Section 1.4 and Chapter 2).

5.1 POM CBM framework for predictive maintenance in industry

In order to facilitate the design and the deployment of a predictive maintenance policy in industry, the POM CBM framework has been developed in the frame of the POM project (*Prognostics for Optimal Maintenance (POM1 & POM2) project* 2011). An illustration of the architecture of this framework is depicted in Figure 5.1. The developed framework is applied to all three case studies presented in this chapter in order to deploy and validate the proposed models.

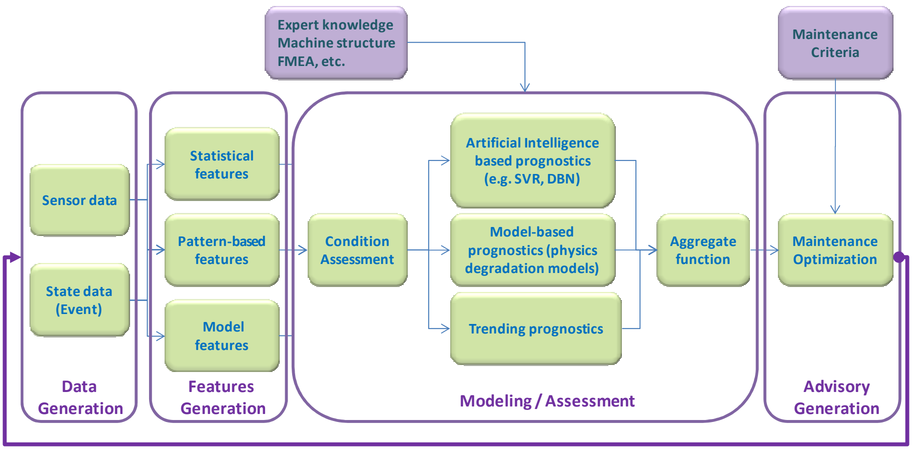

Figure 5.1: Overall architecture of POM CBM framework.

A detailed description of this framework is given by Bey-Temsamani, Bartic, et al. (2011). The framework has been developed following the available standards like ISO 13374 for condition monitoring and diagnostics and OSA-CBM (Open System Architecture for Condition-Based Maintenance) (Sheppard et al. 2009). The different modules of the framework consist of (i) data generation, (ii) features generation, (iii) modeling and assessment and (iv) advisory generation. Every module is considered as independent from the others and can be customized accordingly to the studied application. This is afforded by a proper choice of inputs/outputs interfacing every module and allowing thus flexibility and interoperability. A module can also be divided into sub-modules where some external interactions can be set, like including information from experts in the field if available to make an assessment model more robust. Since the framework is supposed to work online for maintenance optimization, feedback between different modules is foreseen to fortify the prognostics in an iterative and dynamic way against variability and environmental changes in the studied process. In the following sections, only the last module, advisory generation, will be described in detail for the three studied use cases as the prognostic algorithms themselves are out of scope for this dissertation (Section 1.5). The details about the predictive features used for the prognostics part are available respectively in Ostyn et al. (2007) and Bey-Temsamani et al. (2009b) for the two first use cases and in Bey-Temsamani, Van Horenbeek, et al. (2013) for the third use case.

5.2 Maintenance cost versus product quality optimization

Correlation between the quality degradation of a product and maintenance of a machine or sub-components of the machine making this product is often established on assumptions by the production engineers. In most cases these assumptions are summarized in the fact that the quality of the product starts to degrade after a fixed number of operation cycles of the production machine or machine's subcomponents and therefore preventive maintenance on the production machine is only performed after this fixed number of cycles. This kind of assumptions is often not valid in modern industry since high variability of products, tolerances of machines/components, reliability variations of these components, extensive/smooth usage, etc. make this degradation quite dynamic versus time. As a result, the quality of the product could get degraded in a fast way or in a slow way depending on the variability in process parameters. Both cases will lead to low benefit because of lost production in the former case or redundant maintenance in the latter one. In this chapter a solution to this problem is proposed by maximizing the benefit using online monitoring of product's quality degradation and maintenance cost evolution.

Many models for condition-based (CBM) or predictive (PdM) maintenance optimization exist in literature. These make clear that maintenance decision making based on real-time information from the components and systems has a substantial benefit regarding maintenance cost, prevention of unexpected failures and reduction of downtime. However, for some systems it is not due to the state of the system itself that maintenance is needed but due to the quality degradation of the products it is producing. The objective is to determine the benefit of PdM with regard to quality degradation of the produced parts by the monitored system. By doing this the optimal time to perform maintenance is determined by considering the trade-off between maintenance cost and cost of quality degradation of the produced parts. Predictive maintenance optimization in literature is mostly restricted to theoretical modeling of the degradation process, by for example stochastic processes, and subsequently finding an optimal maintenance policy for this degradation process (van der Weide et al. 2010; Bouvard et al. 2011). In most cases the many assumptions made about this failure behavior of components are only valid under certain circumstances. Operation and environmental conditions are assumed to be known and cannot change significantly. In general however this is not true for all machines because usage rates and environmental conditions are changing over time. Together with the shortage of industrial case studies this makes the applicability in industry of such models difficult and creates a gap between theory and practice (Van Horenbeek, Pintelon, and Muchiri 2010; Sharma et al. 2011). Moreover decision making based on real-time information from monitoring systems and components is still an underexplored area in maintenance optimization (Muller et al. 2008). The integration of predictive information into decision support systems is a very important step that needs further research as already stated in Section 1.3. To overcome these flaws two case studies are presented where real-time predictive information coming from the real machines is directly used to support maintenance decision making by including product quality degradation. This support is given by updating a cost function whenever new information about the system performance becomes available. Based on this information maintenance is scheduled in an optimal way. The POM CBM framework (Section 5.1) is used as a tool for predictive maintenance optimization.

The originality and contribution to the field of maintenance lies at different levels:

- A maintenance cost versus product quality degradation PdM optimization is performed, which has, according to the knowledge of the author, never been done before. Although this should certainly be considered in many industrial production machines in order to be able to perform optimal maintenance.
- Degradation is not only caused by wear out, but mainly by usage rates and environmental conditions, which is accounted for in the condition monitoring approach taken in this chapter.
- An integrating approach is taken by developing a decision support system based on condition monitoring information directly coming from the machine without any assumptions on the degradation process. The integration of condition monitoring that results in predictive information on equipment performance and decision making based on this predictive

information is perceived as one of the biggest challenges in maintenance (Muller et al. 2008).

- Few case studies have been reported on maintenance optimization models for predictive maintenance (Van Horenbeek, Pintelon, and Muchiri 2010) (Section 1.4). In this chapter the developed PdM optimization model, including product quality as a decision criterion, is applied to two different real life industrial case studies in order to show the applicability of the developed methodology.

5.2.1 Case studies description

Seal quality monitoring in a packing machine

The first industrial use case consists of a Vertical Form Fill and Seal (VFFS) packing machine. The machine produces bags of different products (chips, cheese, sugar, etc.) in food industry. A plastic film roll is supplied as a packaging material. After forming flaps that wrap around a main conical tube as depicted in Figure 5.2, the film is pulled downward around the outside of the tube and the vertical heat-sealing jaws clamp onto the edges of the film bonding the film by melting the seam edges together. After the bonding, a knife cuts the film forming thus a produced bag.

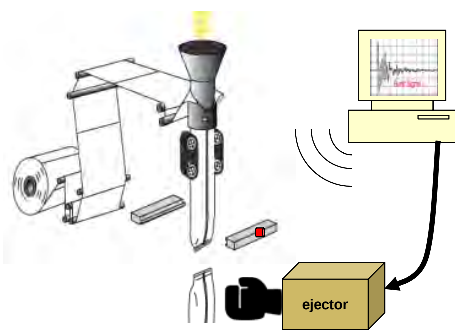

Figure 5.2: Seal quality monitoring in a packing machine.

One of the main rejects in the field is the seal quality of the produced bags. The seal quality degradation is caused by accumulation of dirt and dust that the production environment is subject to and the leakage of the product during the cutting process on the sealing jaws. Hereby their sealing quality reduces and these bad sealed bags have to be thrown away, which results in lost production.

In order to monitor this degradation, a condition monitoring system called SealScope (De Ketelaere et al. 2004) is used. This system measures vibration signatures due to the impacts of the sealing jaws during the bonding process and applies advanced multivariate quality control charts based on recursive principal components analysis with adaptable forgetting technique (Ostyn et al. 2007) to calculate prognostic features correlated to the studied quality degradation.

Print quality monitoring in copiers

The second use case consists of monitoring the quality of the copy papers from a fleet of copiers. This case study was carried out within the frame of the IRIS (Intelligent Remote Industrial Services) project (Bey-Temsamani et al. 2009a; Bey-Temsamani et al. 2009b) where the idea was to provide industrial services (machine's health management, remote configuration, etc.) to the customers of machine builders. An illustration is shown in Figure 5.3. For machine's health management, the main purpose in that project was to identify features which are correlated to the degradation of different components in the copiers and perform predictive maintenance using these predictive features. The quality degradation of the copies due to component degradation was not covered.

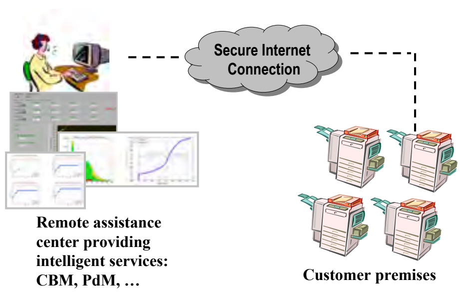

Figure 5.3: Print quality monitoring in copiers.

In this work, the predictive maintenance action will not only be optimized based on the degradation of components but also taking into account the degradation of the copies. As stated by Tse (1998), the monitored component degradation in the copier is directly related to the quality degradation of the product (i.e. bad copied pages). The predictive model that is used here to predict component degradation is described in Bey-Temsamani et al. (2009b).

5.2.2 Cost model for optimal maintenance planning

Maintenance cost versus product quality degradation

For both case studies a cost model is built where the trade-off between the cost of maintenance actions and the cost of quality degradation is considered. The cost function is continuously updated as new information about the condition and performance of the equipment becomes available. This maintenance cost information enables optimal maintenance planning based on the real performance and degradation of the considered components or systems.

Figure 5.4 illustrates the advantage of using predictive information to schedule preventive maintenance actions compared to time-based preventive maintenance scheduling. The predictive information takes into account the changing usage rates and environmental conditions which influence the degradation process, while the time-based maintenance actions assume a fixed degradation over time. The timing of preventive maintenance actions are plotted on the x-axis, where t_M is the time of maintenance based on monitoring information and t_P is the time of the time-based preventive maintenance action. The y-axis shows the decision rule based on the monitored feature. This decision rule can have different implementations like for example a fixed threshold on a condition monitored parameter. For example, for the first case study in this chapter a decision rule based on the maximal profit is implemented, this will be discussed in Section 5.2.2. The predictive maintenance policy prevents, for the first maintenance action, the loss due to quality degradation of the product by performing maintenance earlier compared to the time-based policy. For the second maintenance action the quality degradation is less than anticipated by the time-based policy, a loss due to too much maintenance is incurred here compared to a predictive policy. This shows that a trade-off between the cost of quality degradation and the cost of maintenance should be used in an optimization process to come to an optimal maintenance policy. This is illustrated, together with the ability of the predictive maintenance policy to incorporate the changing quality degradation due to changing usage rates and environmental conditions, in the next sections of this chapter.

Case study one: seal quality monitoring in a packing machine

For the first case study the relevant feature, which is correlated with the performance of the machine, is the percentage of bad bags produced by the sealing machine which is determined by the approach presented in Ostyn et al. (2007). Zero padding is applied to calculate this percentage of bad bags in order to reduce the effect of bad bags at the beginning of production. This feature is

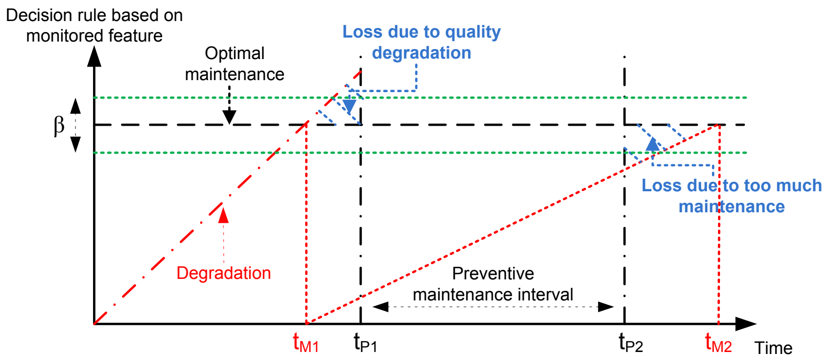

Figure 5.4: Advantage of a predictive maintenance policy over a time-based preventive maintenance policy considering a trade-off between the cost of maintenance actions and the cost of quality degradation for different deterioration rates.

used to represent quality degradation of the produced bags in a cost function as follows:

$$P_t = (P \times (1 - \alpha)) - (C \times \alpha) - (M/n) \tag{5.1}$$

Where t is the time after the previous maintenance action, P_t is the profit per bag (€) at time t, P is the profit for one good sealed bag (€), C is the cost for one badly sealed bag (€), M is the maintenance cost, n is the number of produced bags until time t and α is the percentage of badly sealed bags until time t.

Based on this cost function it is possible to come up with a decision rule, similar to a control-limit policy, which determines when maintenance should be performed. For this specific case study maintenance is performed when:

$$P_t < P_{max} \times (1 - \beta) \tag{5.2}$$

Where t is the time after the previous maintenance action, P_t is the profit per bag (€) at time t, P_{max} is the maximal profit per bag (€) until time t and β is the maintenance percentage.

This means that at each time t, when a bag is produced, the profit per bag P_t is updated according to the new information on the percentage of bad sealed bags α. When P_t becomes smaller than a certain percentage, which is determined by parameter β, of the maximal profit per bag P_{max} until t a preventive maintenance action should be performed. The reason why P_t is allowed to decrease compared to P_{max} is because the considered feature of percentage of bad sealed bags is not monotonically increasing. The maintenance percentage β is the parameter in the decision rule which determines when maintenance should be performed in order to maximize the profit per bag P_t. The determination of the optimal value of β is performed based on data coming from experiments on the packaging machine itself. Simulations on this data were used to determine the value of β which optimizes P_t. Figure 5.5 shows the result of this optimization where $P = 10$€, $C = 10$€. The maintenance cost M for the specific case study performed in this section is €200, which according to the optimization means that a value of 0.02 for the maintenance percentage β is optimal. Of course it is possible to update the value of β continuously when more data become available.

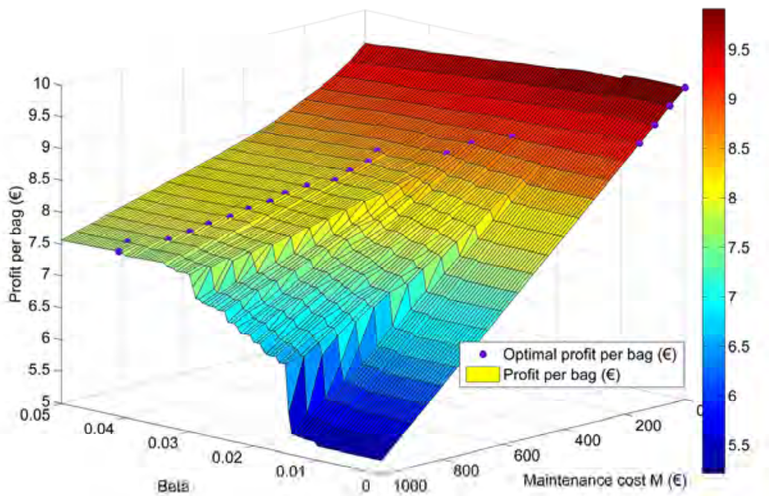

Figure 5.5: Determination of β which maximizes the profit per bag P_t.

In order to quantify the added value of decision making based on real-time evaluation of the earlier introduced cost function and decision rule a comparison is made between this policy and the maintenance actions that were performed in real life. The maintenance actions performed in real life are based on the experience of the operator. When the operator believes that the packaging machine produces too many bad sealed bags a preventive maintenance action is performed. The results of the comparison are given in Figure 5.6, which shows the percentage of bad bags (α) and profit per bag P_t in function of the number of produced bags. Both a reference maintenance scenario, which shows the real life situation, as well as a predictive maintenance policy are presented. The maintenance timing reference that is shown in Figure 5.6 is the timing of the maintenance actions performed based on the experience of the operator without making use of the monitored feature (α) for decision making. A total profit per bag $P_{tot,ref}$, which is the profit of the reference scenario for the entire experiment, is also calculated in order to make comparison with the predictive maintenance policy possible. By using the monitored feature, percentage of bad bags (α), it is possible to implement the predictive maintenance policy to the real life data collected from the packaging machine. The continuously updated profit per bag P_t, which is used to schedule maintenance as described before, is presented in Figure 5.6. Based on the decision rule (Equation 5.2) a preventive maintenance action is scheduled which takes into account the trade-off between the cost of quality degradation and the cost of maintenance. From this simulation it is clear that in general the operator waited too long to perform a preventive maintenance action, which results in a decrease in profit per bag due to quality degradation of the produced bags. A total profit per bag for the entire experiment is calculated for both the reference scenario ($P_{tot,ref} = 8.3435$€) and the predictive maintenance scenario ($P_{tot,PdM} = 8.9006$€). An increase of 6.68% in the total profit is possible by implementing a predictive maintenance policy that incorporates the changing quality degradation due to different usage rates and environmental conditions. This predictive maintenance policy makes it possible to monitor the profit per bag in real-time, which assists the operator to perform maintenance at the optimal time.

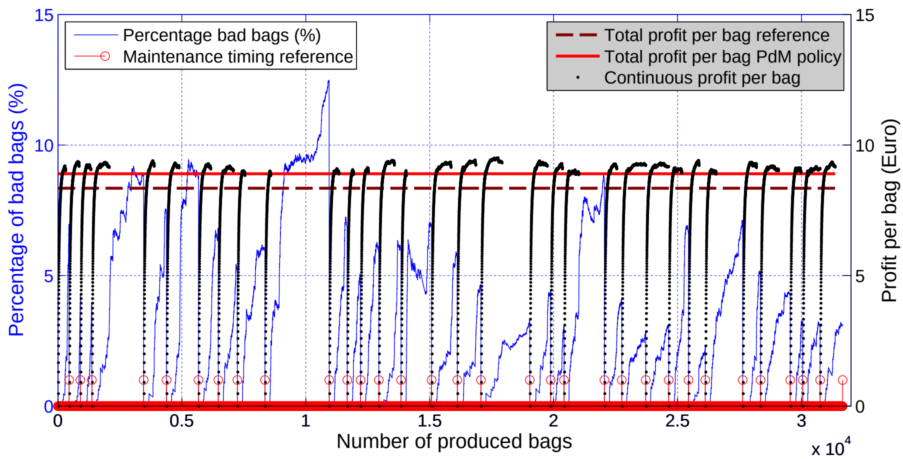

Figure 5.6: Comparison between reference maintenance policy and predictive maintenance policy.

The influence of the cost parameters on the gained profit of the PdM maintenance policy compared to the reference scenario is shown in Figure 5.7. As $P = C$, the effect of the ratio $M/P = M/C$ on the profit is investigated. Compared to the reference scenario it is clear from Figure 5.7 that when the ratio M/P increases, the gain in profit of the PdM policy compared to the reference scenario decreases. This is explained by the fact that when the cost of a maintenance action M becomes relatively (i.e. compared to the other cost parameters P and C) bigger, the optimal time to perform maintenance is postponed and gets closer to the maintenance timing in the reference scenario. Therefore, the gain in Figure 5.7 tends to become zero as M/P increases, which means that the maintenance timing in the PdM policy would become the same as in the reference scenario. Note that from this point onwards it becomes impossible to derive any conclusions as the available data is censored due to the execution of maintenance. This highlights the major limitation of an approach that uses real and censored maintenance data, as no scenario where the maintenance actions are performed later then in the reference scenario can be investigated. This can only be done when the degradation is modeled explicitly, as will be illustrated in Chapter 6.

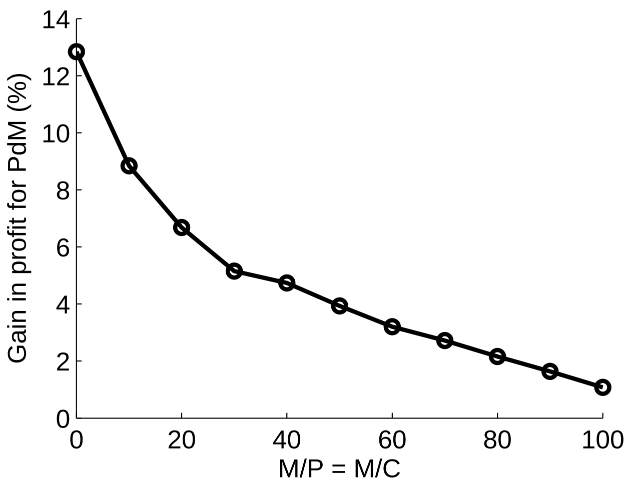

Figure 5.7: Gain in profit (%) of the PdM maintenance policy compared to the reference scenario for different ratios of M/P ($= M/C$).

Case study two: print quality monitoring in copiers

For the second case study the monitored feature is directly correlated to the quality degradation of the product (Tse 1998). For a photocopier quality degradation can be seen as bad copied pages. The general overview on how the predictive information is used to optimally schedule maintenance actions based on a trade-off between maintenance costs and quality degradation costs is shown in Figure 5.8. Figure 5.8a depicts the prediction of the evolution of the monitored feature and the corresponding degradation. A lower threshold (feature value of 800 (x_{t_1})) and an upper threshold (feature value of 1500 (x_{t_2})) are used to describe the quality degradation over time. Before reaching the lower threshold no bad copies are produced, which means the photocopier is in perfect working condition. When the degradation feature reaches the lower threshold, quality degradation of the produced copies starts and evolves through time according to a quality degradation function. This quality degradation function is assumed to be linear and is shown in Figure 5.8b. The quality degradation function describes a linear relation between the monitored feature and the probability of producing bad copies. When the monitored feature reaches the upper threshold the probability of producing bad copies equals 1, which means only bad copies are produced at this time and the photocopier is in a failed state. The time that the feature value reaches the lower threshold is defined as t_1 and the time of reaching the upper threshold is defined as t_2.

Based on the predicted deterioration and the corresponding quality degradation function it is possible to optimally schedule preventive maintenance actions by optimizing a cost function. Each time new monitoring information and a corresponding prediction about the state of the component becomes available the cost function and preventive maintenance timing is updated. The profit function if maintenance is performed at time t_a is defined as follows:

$$P(t_a) = \frac{(n_1 \times P) + ((1 - D(x)) \times n_\Delta \times P) - (D(x) \times n_\Delta \times C) - M}{n_1 + n_\Delta} \tag{5.3}$$

Where $P(t_a)$ is the profit per copy (€) when maintenance is performed at time t_a, n_1 is the number of copies produced until reaching the lower threshold of the monitored feature (i.e. within time t_1), n_Δ is the number of copies produced between t_1 and t_a, P is the profit for one good copy (€), C is the cost for one bad copy (€), M is the maintenance cost (€) including spare part cost and $D(x)$ is the percentage of bad copies between t_1 and t_a.

In this cost function the quality degradation is incorporated by the function $D(x)$, the percentage of bad copies between t_1 and t_a, which reflects the quality

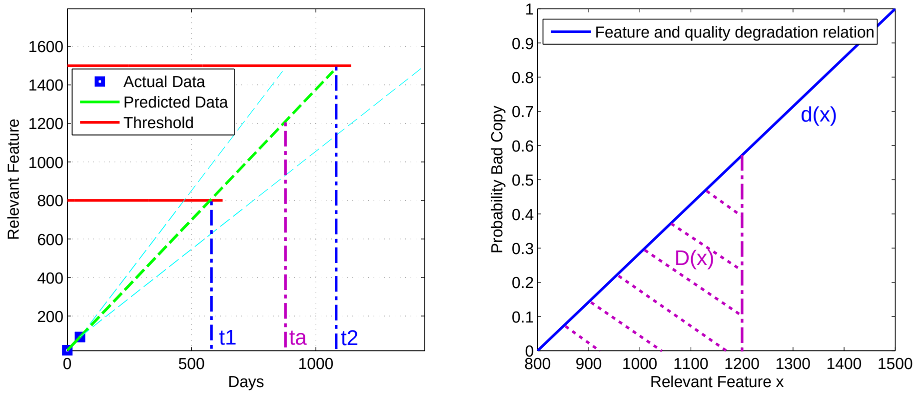

Figure 5.8: (a) Prediction of deterioration (b) Quality degradation function.

degradation function as defined in Figure 5.8b. The function $D(x)$ is calculated as follows:

$$D(x) = \begin{cases} 0, & \forall x \leq x_{t_1} \\ \int\limits_{x_{t_1}}^{x} d(x)dx/(x - x_{t_1}), & \forall x > x_{t_1} \end{cases} \tag{5.4}$$

Where $D(x)$ is the percentage of bad copies between t_1 and t_a, x_{t_1} is the feature threshold value where quality degradation starts at time t_1, x is the feature value at time t_a, $d(x)$ is the quality degradation function.

Based on the deterioration prediction (Figure 5.8a) and the quality degradation function (Figure 5.8b) it is possible to determine the optimal time to perform maintenance by evaluating the cost function defined in Equation 5.3 for different timings of maintenance. The time where the profit curve is maximized is the optimal time to perform preventive maintenance. This is shown in Figure 5.9a and Figure 5.9b. This profit curve, together with the corresponding optimal time to perform preventive maintenance is updated each time new predictive information becomes available.

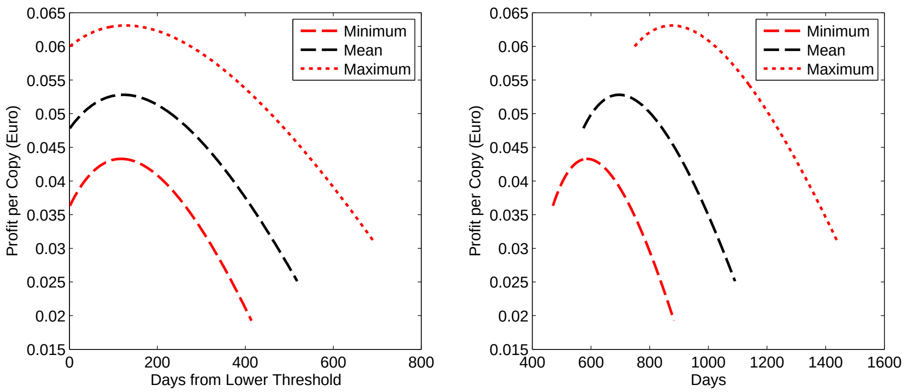

Figure 5.9: (a) Profit curve for relative time unit since lowest threshold (b) Profit curve for absolute time unit.

5.3 Production capacity optimization using temperature condition monitoring

Using condition monitoring to track machine health and trigger maintenance actions received quite some attention during the past years (see Chapter 2). By monitoring machinery health, costly failures are avoided and downtime due to outages is reduced, which finally results in an increase of operational efficiency and productivity of the equipment. However, much less attention is paid to the use of condition monitoring information in order to optimize production capacity of a machine or a plant. Most of the available maintenance models have concentrated solely on reliability data, and have not taken into account other system information (i.e. production requirements) (Yao et al. 2005). Moreover, the available joint models on production and maintenance are mainly focused on time- and use-based maintenance policies and have been built for mathematical elegance rather than for application to real-life case studies (Berrichi et al. 2009; Hadidi et al. 2012). Therefore, the objective is to establish the link between condition monitoring information, maintenance and production capacity optimization by continuously adjusting production parameters (e.g. production speed) according to the measured condition monitoring information. This is done by presenting a case study of steel production machines. Cost-effective temperature sensors are installed for condition monitoring on these machines in order to monitor possible overheating and corresponding failures of the machines. The use of this condition monitoring information is extended (i.e. not only avoiding failures) in order to maximize the production capacity by optimizing the machine's speed. Without optimization (i.e. the current way of working), the machine is simply stopped when overheating is detected. This results in lost production capacity. Therefore, the condition monitoring information is used as an input to the machine's controller in order to optimize the production speed. The speed of the production machine is namely directly related to the corresponding temperature increase or decrease. Optimization of the production speed results in maximal production capacity and minimal machine downtime by prevention of overheating and corresponding failures. It is clearly illustrated in the following sections how temperature condition monitoring information can be used to maximize industrial production capacity. This approach extends the use of condition monitoring information from purely avoiding unexpected failures to productivity optimization of an entire system by inclusion of production parameters into the optimization problem.

5.3.1 Production capacity optimization approach

Different measures of productivity exist in the available literature. The overall equipment effectiveness (OEE) concept has been widely used as a quantitative tool essential for measurement of productivity (Muchiri and Pintelon 2008). The OEE measurement tool evolved from the total productive maintenance (TPM) concept introduced by Nakajima (1988) and is defined as a measure of total equipment performance, that is, the degree to which the equipment is doing what it is supposed to do (Muchiri and Pintelon 2008). It is a three part analysis tool in order to determine equipment performance based on its availability, performance and quality rate of the output. It is used to identify the related equipment losses for the purpose of improving and optimizing the total productivity and performance of the considered system. Six major categories of losses are identified within the OEE concept; these are depicted in Figure 5.10 and can be summarized as follows (Muchiri and Pintelon 2008):

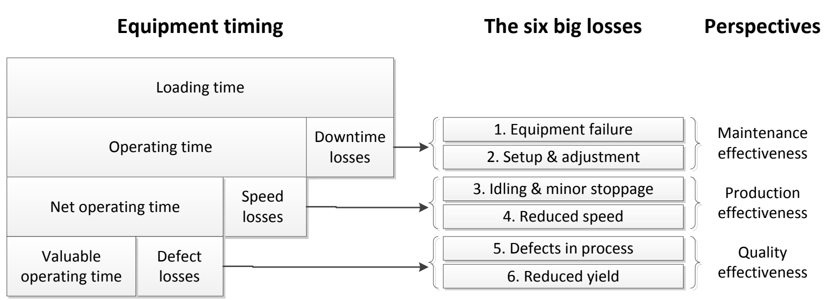

Figure 5.10: OEE concept for performance measurement.

- *Breakdown losses* categorized as time losses and quantity losses caused by equipment failure or breakdown.
- *Set-up losses* occur when production is changing over from one item to another.
- *Idling and minor stoppage losses* occur when production is interrupted by temporary malfunction or when a machine is idling.
- *Reduced speed losses* refer to the difference between equipment design speed and actual operating speed.
- *Quality defects and rework* are losses in quality caused by malfunctioning production equipment.
- *Reduced yield* during start-up are yield losses due to machine start-up.

$$OEE = A \times P \times Q \tag{5.5}$$

Where:

$$Availability\, rate\; (A) = \frac{Operating\, time\; (h)}{Loading\, time\; (h)} \times 100 \tag{5.6}$$

$$Performance\; (P) = \frac{Theoretical\; cycle\; time\; (h) \times Actual\; output\; (units)}{Operating\, time\; (h)} \tag{5.7}$$

$$Quality\, rate\; (Q) = \frac{Total\, production\; (units) - Defect\; amount\; (units)}{Total\, production\; (units)} \tag{5.8}$$

The six major losses can also be defined for the considered case study of steel production machines as follows:

- *Breakdown losses* caused by equipment failure or breakdown due to overheating.
- *Set-up losses* occur between production cycles.
- *Idling and minor stoppage losses* occur when production is interrupted due to ruptures of the produced wire.
- *Reduced speed losses* occur when the operator lowers the speed to avoid overheating.
- *Quality defects and rework* are losses in quality caused by for example wire ruptures.
- *Reduced yield* due to machine start-up.

By considering the six major losses defined in OEE an optimal performance of the process can be achieved by monitoring and corresponding optimization of process and system parameters. This can be done by defining an efficient maintenance schedule, a good output (product) quality and an optimal production speed. Many papers on optimal maintenance scheduling are discussed in literature (Van Horenbeek, Pintelon, and Muchiri 2010). Furthermore, research on optimizing maintenance with regard to output quality has been presented in (Section 5.2). Therefore, here we will focus on production speed optimization to maximize OEE (i.e. in order to maximize production capacity) through condition monitoring for the case study of steel production machines.

5.3.2 Validation on an industrial case study

The analyzed case study is performed within the wire processing industry. The goal is to clearly illustrate how temperature condition monitoring information can be used to maximize industrial production capacity. This approach extends the use of condition monitoring information from purely avoiding unexpected failures to productivity optimization of an entire system.

Problem formulation

In the wire processing industry, production cycles are repeated in order to produce a product (i.e. a wire spool). Currently, during these cycles the temperature and the speed of the machines are recorded. The temperature sensors are only monitoring possible overheating of the machine in order to prevent failures (Bey-Temsamani, Van Horenbeek, et al. 2013), which means the operator reduces the speed to prevent temperature overheating (i.e. temperature rises close to the temperature threshold) or the machine is simply stopped when overheating (i.e. temperature rises above the temperature threshold) is detected. Both result in lost production capacity. The usefulness of the temperature condition monitoring data is extended by proposing a model that uses this data to optimize the machine's production speed while at the same time avoiding temperature overheating. The speed of the production machine is namely directly related to the corresponding temperature increase or decrease. As such, optimization of the production speed results in maximal production capacity and minimal machine downtime by prevention of overheating. The problem is schematically depicted in Figure 5.11.

The information about speed and temperature gathered in previous runs is used to propose an optimal production speed, while avoiding overheating, for current and potentially future runs. The machine health is supposed to be within the

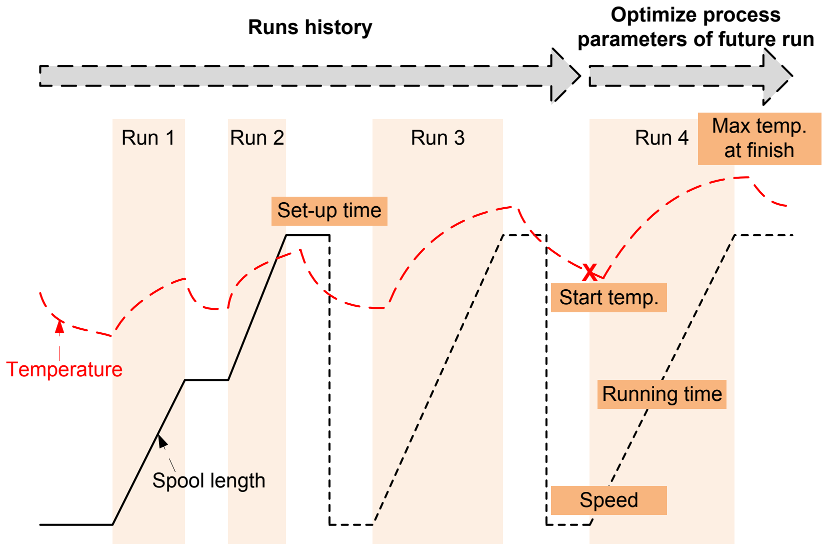

Figure 5.11: Production speed optimization by avoiding machine's overheating.

safe band when the temperature does not exceed a fixed temperature value or threshold, defined by the original equipment manufacturer (OEM). However, the proposed model could be extended to take into account the dynamic change of machine's health by simply changing the fixed threshold to a varying function versus time which describes the health degradation if this is known. In order to solve the problem described in this section, a model of the temperature versus the production speed is needed.

Temperature - speed model

After an extensive data cleansing and preparation by removing all kind of outliers and dividing properly the data into subsets corresponding to different runs, a parametric model has been developed to model the machine's temperature versus the production speed. It is estimated by nonlinear mixed effects models that allowed describing the run-to-run variability in the data (Lindstrom and Bates 1990). Parameters are estimated using Restricted Maximum Likelihood (REML). The results showing the modeled temperature versus the measured ones are shown in Figure 5.12. The model describes quite accurately the temperature versus the speed data with a coefficient of determination $R^2 = 0.9815$. Figure 5.13 shows an example of the temperature versus speed model for two different initial temperatures at the start of the production cycle.

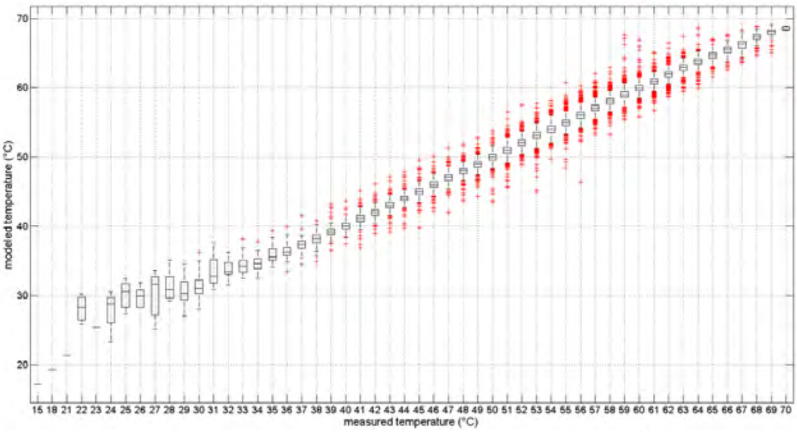

Figure 5.12: Modeled versus measured temperature.

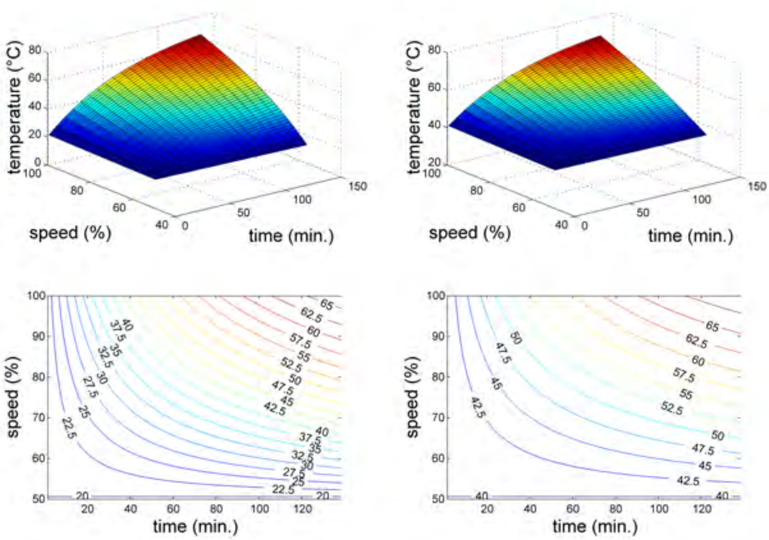

Figure 5.13: Speed versus temperature model for (a) an initial temperature of 20°C (b) an initial temperature of 40°C.

Production speed optimization

The production speed optimization consists of proposing a production speed for the current and future cycles that maximizes machine's capacity without the risk of overheating. Based on the temperature at the start of the cycle and the wire length to produce, the temperature during and at the end of the run can be determined, for a given speed, by the temperature - speed model (Section 5.3.2). The determination of the optimal production speed v^*, while avoiding overheating, can be formulated as a constrained maximization problem as follows and is illustrated in Figure 5.14:

$$v^* = \max\{v|[t_s(v, l_s) < t_T(v, l_s, T_i)] \wedge (v \geq 0) \wedge (l_s \geq 0)\} \tag{5.9}$$

Where v is the production speed for the next production run, l_s is the spool length set point for the next production run and T_i is the initial temperature at the start of the production run. t_s is defined as the time to finish the production run and is function of v and l_s. t_T is defined as the time to reach the temperature threshold and is function of v, l_s and T_i.

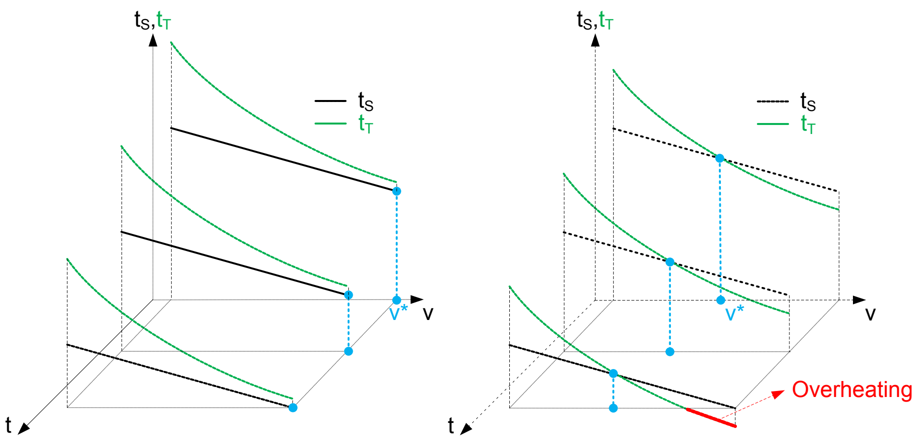

Figure 5.14: Production speed maximization problem.

Simulation based optimization of the running speed based on recorded process data, collected over a time period of ten months, is performed to illustrate the benefit of the presented capacity optimization approach compared to the current way of working. In this simulation all production losses as defined in Section 5.3.1 are considered. This means that all production losses, except for the speed losses, are the same in both the simulation and the measured data. The speed is optimized according to the presented approach. Single run optimization is considered, which means that the optimal speed is defined for only the next run based on the current temperature at the start of the run. After each run the temperature and corresponding optimal speed is updated. The results in terms of produced spool length per time unit (i.e. m/min) are shown in Figure 5.15. In the current way of operation the capacity of the machine over the considered period of ten months is 71.43 m/min, while in the optimized scenario the capacity increases to 92.23 m/min. This corresponds to a possible gain in production capacity of 29.12% by maximizing production speed while at the same time avoiding overheating and corresponding failures. It is clear that the proposed optimization methodology shows a high potential to increase production capacity. However, the model still needs to be validated in the real plant to confirm these simulation based results.

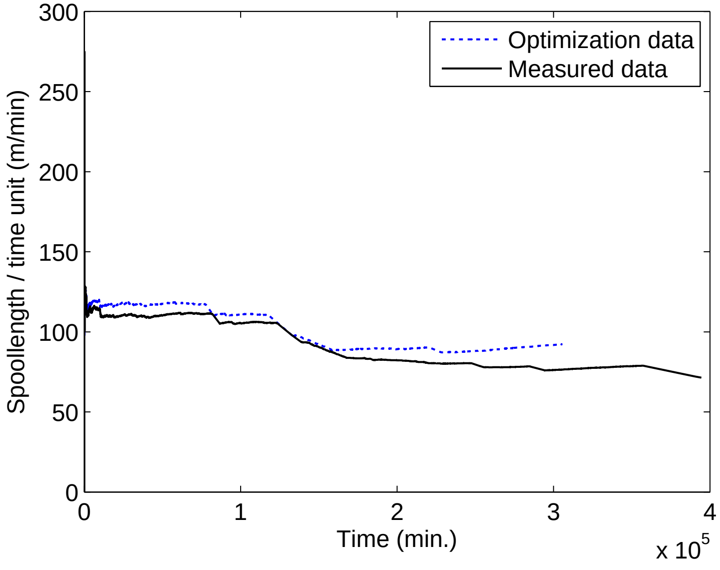

Figure 5.15: Comparison between current way of working and capacity optimization approach.

5.4 Conclusions

This chapter presents predictive maintenance models for real-time and dynamic maintenance decision making. The developed models are specifically applied to three case studies in order to illustrate their applicability in real-life case studies. In this way the performed simulations and optimizations are based on real process data. The first two models and case studies address the trade-off between maintenance cost and product quality degradation cost. Based on the developed profit maximization technique, it is possible to optimize maintenance in real-time by monitoring the degradation of the product. It is shown that the added value of the predictive information in maintenance scheduling and optimization regarding the trade-off between maintenance cost and quality degradation cost is substantial. The third case study extends the use of condition monitoring from purely avoiding failures and scheduling maintenance to production capacity optimization. Temperature monitoring is used to optimize production capacity in wire process industry. The use of predictive information shows major potential to increase production capacity, however, the proposed model still needs to be validated in the real production plant. Finally, it can be concluded that for certain applications maintenance optimization should not only take into account the health of the machines and components, but should also include final product quality and production capacity as optimization parameters.

The developed models proved to be able to deal with real data from industrial cases where complexities in predictive features like local minima, measurement noise and abrupt usage changes could take place. In this way one of the major issues in maintenance management, applicability of the developed models in real-life problems (Section 1.4), is clearly addressed. Moreover, the scope of the commonly available maintenance optimization models is extended by considering both product quality and production capacity as maintenance objectives in the decision problem (Section 1.4). However, it is also worthwhile to mention the limitations of the presented models. It is not always straightforward to determine the long-term performance as the presented models depend on real-time data that is often censored due to the execution of maintenance or not available for long time periods. In order to be able to determine long-term performance an explicit formulation of the degradation process is necessary (see Chapter 6). Moreover, the baseline scenario is determined by the actions of the operator and this behavior is very difficult to model. Finally, the developed models do not address interactions between components or systems as they only consider single-component and single-system applications. The effect of component interactions in maintenance optimization is the subject of Chapter 6.

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Chapter 6

A dynamic predictive maintenance policy for complex multi-component systems

Chapter 4 presented a model for long-term performance evaluation of predictive maintenance, while Chapter 5 focused on models for real-time maintenance decision making based on predictive information. However, both type of models also have their limitations. The former are limited to long-term performance determination without the possibility of defining maintenance schedules and incorporating maintenance opportunities, as a static model is considered. For the latter, it is however difficult to determine the long-term performance as real maintenance data are a prerequisite and these are generally not available for long time periods. Therefore, based on the understanding gained from the previously presented models, a dynamic predictive maintenance policy is presented, usable for both long-term performance evaluation and dynamic maintenance scheduling.

The use of prognostic methods in maintenance in order to predict remaining useful life already received reasonable attention over the past years. However, the use of these techniques for maintenance decision making and optimization

This chapter is based on A. Van Horenbeek and L. Pintelon (2013b). "A dynamic predictive maintenance policy for complex multi-component systems". In: *Reliability Engineering & System Safety* 120, pp. 39–50 in multi-component systems is still an underexplored area of research (Section 1.3). Therefore, the objective is to optimally plan maintenance for a multi-component system based on prognostic/predictive information while considering different component interactions and dependencies (i.e. economic, structural and stochastic dependence). Consequently, this chapter presents a dynamic predictive maintenance policy for complex multi-component systems that minimizes the long-term mean maintenance cost per unit time. The proposed maintenance policy is a dynamic method as the maintenance schedule is updated when new information on the degradation and remaining useful life of components becomes available. In this way, the developed model directly addresses the second research question which is defined as follows:

> "*Determine the added value of predictive information on component degradation in the form of remaining useful life (i.e. information-based) in maintenance decision making by developing and optimizing a dynamic predictive maintenance policy (PdM) for complex multi-component systems that can be used for both long-term performance evaluation of PdM, as for real-time and dynamic maintenance decision making.*"

The performance, regarding the objective of minimal long-term mean cost per unit time, of the developed dynamic predictive maintenance policy is compared to five other conventional maintenance policies, these are: block-based maintenance, age-based maintenance, age-based maintenance with grouping, inspection condition-based maintenance and continuous condition-based maintenance. The ability of the predictive maintenance policy to react to changing component deterioration and dependencies within a multi-component system is quantified and the results show significant cost savings.

6.1 Setting the scene

6.1.1 Problem statement

The complexity of industrial equipment is ever increasing, which introduces many interdependencies between the components (also see Chapter 4). Neglecting these interdependencies when scheduling maintenance actions leads to inefficient maintenance (e.g. higher costs and downtime). Maintenance policies should be adapted to take into account these interactions between components and equipment in order to find a system-wide and even plant-wide optimal maintenance policy. A multi-component and system approach needs to be taken in maintenance optimization models. Nicolai and Dekker (2007) give an overview of optimal maintenance policies for multi-component systems based on the dependence between components (i.e. stochastic, structural or economic dependence). However, no models that use prognostic/predictive information or a prediction of remaining useful life (RUL) are mentioned. This is striking as the use of prognostics in maintenance is increasing over the past years (Jardine, D. Lin, et al. 2006; Lee et al. 2006; Muller et al. 2008). Therefore, the link between prognostic algorithms and decision making based on the resulting remaining useful life distributions should be established in a predictive maintenance policy (see Section 1.6.2).

Currently a lot of attention is paid to condition-based maintenance in literature, and more recently to predictive maintenance policies. A thorough literature overview of both condition-based and predictive maintenance policies is already given in Chapter 2. Some particularly interesting papers handling condition-based and predictive maintenance for multi-component systems are described. A multi-component systems approach for condition-based maintenance optimization is applied by Tian and Liao (2011) where economic dependence between components exists. Yang et al. (2008) schedule maintenance based on the predicted machine degradation by taking into account the complex interaction between components, production process and maintenance operations. Bouvard et al. (2011) introduce a dynamic condition-based maintenance planning model which uses updated failure probability functions based on component degradation, where the groups of maintenance operations are rescheduled at each decision moment. Although condition-based maintenance takes advantage of the known state of components, setting a degradation threshold beyond which preventive maintenance is carried out is not always an optimal solution compared to predictive maintenance. Certainly not when considering interdependent multi-component systems (Camci 2009). Predictive maintenance makes use, in addition to current degradation information, of predictive information in the form of the remaining useful life of components to optimally schedule maintenance actions, while condition-based maintenance only uses current component state information. Proactive maintenance decisions can be made based on the predictive information which results in a dynamic maintenance schedule. Moreover, the predictive information makes it possible to take into account component interdependencies into the maintenance schedule, as will be illustrated in the remainder of this chapter.

6.1.2 Objective

Although some initial research has been done on condition-based and predictive maintenance policies it is clear that the use of predictive information in advanced maintenance policies for multi-component systems is still an underexplored area of research (Nicolai and Dekker 2007; Jardine, D. Lin, et al. 2006).

Moreover, modeling the combination of dependencies between components is an open area identified in literature, since combining more than one makes the models too complicated to analyze or solve (Nicolai and Dekker 2007; Dekker, Wildeman, and van der Duyn Schouten 1997). The aim of this chapter is to develop a dynamic predictive maintenance policy, which builds further on the research performed by Wildeman et al. (1997) and Bouvard et al. (2011), for a complex multi-component system considering different levels and combinations of dependencies between the components. The dependence between components is modeled as specified by Nicolai and Dekker (2007), where stochastic, structural and economic dependence are defined. *Stochastic dependence* considers the effect of the deterioration of a component on the lifetime distribution of other components. If components structurally form a part or subassembly in a way that maintenance of a failed component implies maintenance on working components, *structural dependence* between those components exists. While *economic dependence* implies that grouping maintenance on components either saves costs or results in higher costs compared to individual maintenance. By taking into account different levels of dependence (i.e. from no dependence over partial dependence to maximal dependence) between components, not only the capability to adapt to different deterioration patterns for several components, but also the capability to adapt to different interactions between components of the dynamic predictive maintenance policy is illustrated. The considered objective is to minimize the long-term mean maintenance cost. To validate the performance of the dynamic predictive maintenance policy it is compared, for the same system but with different dependencies between the components, to five conventional maintenance policies. This allows to quantify the added value of predictive information in maintenance optimization and decision making for complex multi-component systems. The considered maintenance policies are the following; block-based maintenance, age-based maintenance, age-based maintenance with grouping, inspection condition-based maintenance and continuous condition-based maintenance.

The developed predictive maintenance policy is a dynamic maintenance policy, as information that becomes available on the short term (i.e. component degradation information and RUL) is taken into account to adapt the maintenance planning (i.e. similar to the models presented in Chapter 5). Non-stationary situations, such as changing deterioration of components, varying use of components and opportunistic maintenance, can be incorporated. In this way, dynamic decisions are generated that may change over the planning horizon. This is in contrast with stationary models, where a long-term stable situation is assumed (Dekker, Wildeman, and van der Duyn Schouten 1997). Within dynamic models, a further distinction between finite-horizon and rolling-horizon approaches can be made (Dekker, Wildeman, and van der Duyn Schouten 1997). The considered predictive maintenance policy uses a rolling-horizon approach to schedule maintenance actions. These rolling-horizon models use a finite horizon, based on a long-term (i.e. infinite-horizon) plan, which is updated repeatedly as a maintenance action is performed or new short-term information becomes available. Rolling-horizon models aim to bridge the gap between finite- and infinite-horizon models and to combine the advantages of both, which yields more stable solutions compared to finite-horizon models (Dekker, Wildeman, and van der Duyn Schouten 1997).

6.1.3 State-of-the-art advancements

Compared to the papers found in literature and briefly discussed in Section 6.1.1, the research in this chapter advances the state-of-the-art by developing a dynamic predictive maintenance policy, building on the research of Wildeman et al. (1997) and Bouvard et al. (2011), for a complex multi-component system. The main contributions can be summarized as follows:

- A dynamic predictive maintenance policy for complex multi-component systems, specifically addressing the second research question of this dissertation, is presented.
- A combination of different dependencies (e.g. economic, stochastic and structural dependence) between the components in the system is considered in order to determine the added value of the developed predictive maintenance policy within different environments and configurations of multi-component systems.
- Partial dependence has never been considered in maintenance optimization. In previous studies found in literature the dependency in multi-component systems is assumed to exist or not. A major contribution is in this regard the incorporation of partial dependence in the decision making process.
- Imperfect maintenance is included in the developed model. Moreover, the effect of imperfect maintenance on the objective of minimal long-term mean cost per unit time is quantified.
- Dynamic models have been introduced in order to change maintenance planning according to short-term information, by using a rolling-horizon approach (Wildeman et al. 1997). This approach is however only applicable when maintenance durations are assumed to be negligible. In order to resolve this issue, the developed dynamic predictive maintenance policy considers non-zero maintenance downtimes which introduces dependencies between the occurrence dates of the maintenance activities. Moreover, downtime is included as a cost factor in the optimization problem.

- A random failure condition or threshold is considered in order to include its dependence on uncertain operation conditions and deterioration changes.
- The performance of the predictive maintenance policy is compared to five other conventional maintenance policies for different levels of dependence (i.e. ranging from no to maximal dependence) between the components in the system.

Section 6.2 of this chapter describes the degradation and maintenance model. The need for grouping maintenance is discussed in Section 6.3, while the developed dynamic predictive maintenance policy is discussed in Section 6.4. Section 6.5 elaborates on the component dependencies in the considered multi-component system and Section 6.6 handles the maintenance policies used for performance comparison of the developed predictive maintenance model. A numerical example is given in Section 6.7. Finally, the conclusions and future work are stated in Section 6.8.

6.2 Degradation and maintenance model

Consider a system with n non-identical components. A failure of component i causes the entire system to stop (i.e. n-component series system) and a system and/or component failure is noticed immediately without any inspection. Time is discretized with a sample time τ. Component degradation information is retrieved at each inspection date $T_{insp,z} = z\varepsilon_i, z \in \mathbb{Z}^+$ and ε_i is defined as the component inspection period such that $\varepsilon_i = s\tau, s \in \mathbb{Z}^+$. In order to perform maintenance on one component of the system, the entire system has to be stopped, which means system downtime is accrued. Moreover, during this downtime due to maintenance, the deterioration of the non-replaced components remains unchanged. Spare parts are assumed to be available whenever they are needed (this assumption is relaxed in Chapter 7). The degradation and imperfect maintenance model of the i-th component is illustrated in Figure 6.1 and is discussed into more detail in the following sections.

6.2.1 Degradation model

The component degradation is characterized by a physical variable D_i with $i = \{1, \ldots, n\}$, where $\{D_i(t), t \geq 0\}$ is a stationary gamma process with shape parameter ν and scale parameter μ and the following properties (van Noortwijk 2009):

- $D_i(0) = 0$

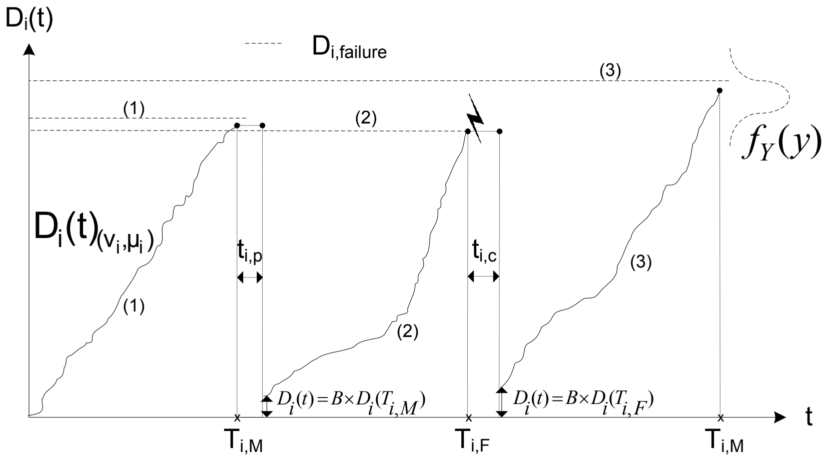

Figure 6.1: Illustration of the degradation model for component i with random failure threshold $D_{i,failure}$, non-zero maintenance downtimes and imperfect maintenance model characterized by improvement factor $B(\gamma, \delta)$. $t_{i,p}$ is the downtime due to a preventive maintenance action and $t_{i,c}$ is the downtime caused by a corrective action.

- $D_i(t)$ has independent increments
- For $t > 0$ and $h > 0$, $D_i(t+h) - D_i(t)$ follows a gamma distribution with shape parameter ν and scale parameter μ

A component i is said to be failed when the degradation level D_i exceeds the failure threshold $D_{i,failure}$. This deterioration failure threshold $D_{i,failure}$ is, opposed to most of the used degradation models in literature, modeled as a random variable. In this way we consider a component with wear-dependent failure rate as defined in Kong and K. S. Park (1997) and Abdel-Hameed (1975). This approach is believed to better model the real degradation process of components as the failure threshold $D_{i,failure}$ depends on the variable operating load, uncertain operating conditions and variable component strength. These factors make that each component fails at a variable degradation level $D_{i,failure}$, rather than when a fixed degradation threshold is reached. For each $t \geq 0$, the probability of failure in time interval $(0, t)$ can then be written as the convolution integral (van Noortwijk 2009; Abdel-Hameed 1975):

$$\begin{aligned} Pr\{X(t) \geq Y\} &= \int_{x=0}^{\infty} f_{X(t)}(x) Pr\{Y \leq x\} \, dx \\ &= \int_{x=0}^{\infty} \int_{y=0}^{x} f_{X(t)}(x) f_Y(y) \, dy \, dx \end{aligned} \tag{6.1}$$

Where $X(t) = D_i(t)$ (i.e. the deterioration at time $t, t \geq 0$) and the probability density function of $D_i(t)$ is given by a gamma distribution with shape parameter ν and scale parameter μ (van Noortwijk 2009), and $Y = D_{i,failure}$ has probability density function $f_Y(y)$. The random variable $D_{i,failure}$ is modeled by a Weibull probability distribution with shape parameter α and scale parameter β in analogy to Kong and K. S. Park (1997) and K. S. Park (1988). Based on the inspection of the current degradation level $D_i(t) = d_i^0$, the failure probability function $F_i(t)$ is computed by stochastic simulation of the degradation process over time. Each time new information on the current degradation level d_i^0 is available - e.g. by inspection - a prediction of the remaining useful life is made. This prognosis is used in the presented predictive maintenance policy as short-term information in order to schedule maintenance actions on a rolling-horizon.

6.2.2 Imperfect maintenance

Each maintenance action, corrective or preventive, reduces the degradation level of component i by a factor $(1 - B)$, $0 \leq B \leq 1$, of the total degradation at the time of maintenance. B is considered as the improvement factor, when $B = 1$ a minimal maintenance action is conducted, when $B = 0$ a perfect maintenance action is performed and when $0 < B < 1$ an imperfect maintenance action is performed. The combination of this imperfect maintenance model with the random failure threshold $D_{i,failure}$ also introduces the possibility of worse and worst repair or maintenance (Pham and H. Wang 1996). This imperfect maintenance model makes that the degradation of component i after maintenance, either corrective or preventive, equals:

$$D_i(t) = B \times D_i(\min(T_{i,M}; T_{i,F})), \forall i \in \{1, \ldots, n\} \tag{6.2}$$

Here $T_{i,M}$ is the time to preventive maintenance and $T_{i,F}$ is the time-to-failure of component i. The improvement factor has a probability density distribution $f(b)$ which is modeled in this chapter by a beta distribution (i.e. because the domain is $[0, 1]$) with parameters γ and δ. In this way imperfect maintenance or replacement is included in the developed model.

6.3 The need for grouping maintenance activities

In order to take the economic and structural interdependencies between components in a multi-component system into account, grouping of maintenance actions should be considered to find an optimal maintenance policy. Therefore, the presented predictive maintenance policy is based on a dynamic policy for grouping maintenance activities (Wildeman et al. 1997). This dynamic policy is extended by including predictive information on the component remaining useful life (Bouvard et al. 2011). One specific preventive or corrective maintenance action can be performed on each component i of the system. A preventive maintenance action has a component-dependent cost $c_{i,p}$ and a system-dependent or set-up cost S. A corrective maintenance intervention has a component-dependent cost $c_{i,c}$ and a set-up cost S. The cost S depends on the performed action and is independent of the number of actions at the same time (e.g. economic and structural dependence). The component-dependent cost c_i depends on the preventive replacement time t and the time-to-failure $T_{i,F}$ of the considered component:

$$c_i(t) = \begin{cases} c_{i,p}, \forall t < T_{i,F} \\ c_{i,c}, \forall t \geq T_{i,F} \end{cases} \tag{6.3}$$

The objective is to group maintenance activities to reduce the maintenance cost (total set-up cost). This means when m maintenance operations are performed at their individual optimal times t_i^* on the considered finite planning horizon PH, the cost equals:

$$C_1 = \sum_{i=1}^{m} c_i(t_i^*) + m \times S \tag{6.4}$$

The possibility of grouping maintenance activities in order to reduce the maintenance cost over PH is considered by defining a *group* of activities as a subset of $\{1, \ldots, n\}$. A *partition* of $\{1, \ldots, n\}$ is a collection of mutually exclusive groups $G_1, \ldots, G_j$, which cover all activities. Finally, a *grouping structure* is defined as a partition of $\{1, \ldots, n\}$ such that all activities within each considered group are jointly executed at time $t_{G_j}^*$, which is defined as the optimal maintenance execution time of group G_j. To determine the maintenance cost when grouping maintenance activities, a grouping structure GS_k, built at each inspection date T_k, is defined with u groups of maintenance actions $G_j, j \in \{1, \dots, u\}$ on PH. In this way the grouping maintenance cost is defined as:

$$C_2 = \sum_{j=1}^{u} \sum_{i \in G_j} c_i(t^*_{G_j}) + u \times S \tag{6.5}$$

For each group G_j of n components a cost C_{G_j} is saved:

$$C_{G_j} = (n-1) \times S - \sum_{i \in G_j} (c_i(t^*_{G_j}) - c_i(t^*_i)) \tag{6.6}$$

Where $(n-1) \times S$ are the savings by grouping n maintenance actions and $c_i(t^*_{G_j}) - c_i(t^*_i)$ is the additional cost of shifting maintenance activity i from the individual optimal time t^*_i to the optimal group maintenance time $t^*_{G_j}$. The predictive maintenance policy aims at finding the grouping structure that minimizes the maintenance cost C_2 on PH.

6.4 Dynamic predictive maintenance policy

The developed dynamic predictive maintenance policy consists of a static long-term maintenance plan and updates this plan at regular time intervals by the incorporation of a dynamic short-term planning on a rolling-horizon. The dynamic short-term planning incorporates the predictive information into the maintenance planning. The main steps in the dynamic policy are shown in Figure 6.2. These steps are similar to the ones described by Wildeman et al. (1997) and consist of:

- Prediction of remaining useful life by estimation of the failure probability function
- Individual maintenance optimization by decomposition and construction of tentative maintenance plan
- Calculation of penalty functions
- Maintenance activities grouping
- Maintenance execution and rolling-horizon update

Although the phases are the same as described by Wildeman et al. (1997), the procedures and calculations followed within these steps are different because of the extensions made in this chapter (e.g. incorporation of predictive information, imperfect maintenance and maintenance downtimes). All these steps are described into more detail in the following sections.

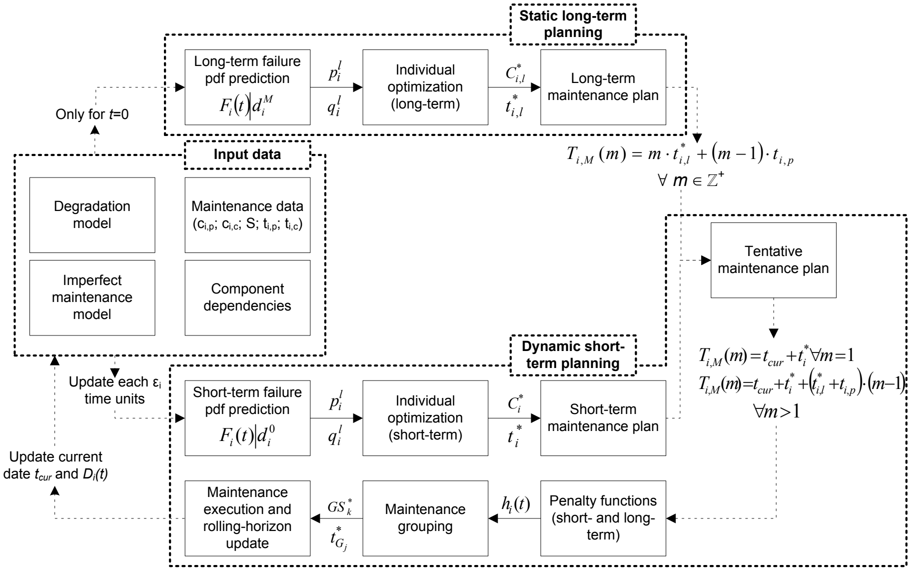

Figure 6.2: Dynamic predictive maintenance policy overview.

6.4.1 Prognostics, prediction of remaining useful life

The proposed predictive maintenance policy is considered as a dynamic maintenance policy, as every time new information on the observed degradation $D_i(t)$ of a component becomes available, the prediction of the remaining useful life of the component is updated, as illustrated in Figure 6.2. The degradation model described in Section 6.2.1 is used to predict remaining useful life $F_i(t)|d_i^0$, by numerical evaluation of (6.1) for each component i, based on the current degradation d_i^0. The stochastic simulation procedure to determine $F_i(t)|d_i^0$ is shown in Figure 6.3. The dynamic or adaptive scheduling of maintenance actions is based on the updated failure probability distribution $F_i(t)|d_i^0$ based on the monitored current degradation d_i^0 of component i.

6.4.2 Individual maintenance optimization

First, an optimal maintenance date on an infinite horizon is determined by decomposing the multi-component maintenance problem into n single-component maintenance optimization models considering an age-based replacement policy. This decomposition approach allows the scheduling of many components (Dekker, Wildeman, and van Egmond 1996). An average use (Wildeman et al. 1997) of the components (i.e. based on population-wide reliability statistics) is assumed and the dependencies and interactions between the components are neglected at this stage. In this way, the savings from joint execution of maintenance activities are ignored. Both a short-term (t_i^*) and long-term ($t_{i,l}^*$) optimal maintenance time are determined. The short-term optimal maintenance time takes into account the current degradation d_i^0, while for the determination of the long-term optimal maintenance age no information on the degradation level is available.

For an age-based replacement policy the asymptotic cost, where t_i^* is the minimizing argument, is given by van der Duyn Schouten and Vanneste (1990). In this chapter this is extended to include non-zero maintenance downtimes into the optimization problem as follows:

$$C_i\left(t|D_i(t)\right) = \frac{c_{i,p} + S + b_i\left(1 - \prod_{l=0}^{t-1} p_i^l\right)}{1 + \sum_{j=2}^{t}\prod_{l=0}^{j-2} p_i^l + \prod_{l=0}^{t-1} p_i^l \cdot t_{i,p} + \left(1 - \prod_{l=0}^{t-1} p_i^l\right) \cdot t_{i,c}}, \forall t = z\cdot\tau, z \in \mathbb{Z}^+ \tag{6.7}$$

The optimal maintenance time t_i^* for a component with degradation $D_i(t) = d_i^0$ is deduced from the following equation:

$$\frac{\mathrm{d}C_i}{\mathrm{d}t}\left(t_i^*|D_i(t) = d_i^0\right) = 0 \tag{6.8}$$

where the empty sum in (6.7) equals zero and the empty product equals one. In (6.7) $c_{i,p}$ is the component dependent preventive maintenance cost and $b_i = c_{i,c} - c_{i,p}$, with $c_{i,c}$ the component dependent corrective maintenance cost. The set-up cost S depends on the type of maintenance and corresponding downtime (see Section 6.5.2 and Equation 6.18). t is the age at which preventive maintenance is performed, $t_{i,p}$ is the downtime due to a preventive maintenance action and $t_{i,c}$ is the downtime caused by a corrective action. p_i^l is the probability that component i survives the next period τ given that its age equals l at the beginning of the current period and $q_i^l = 1 - p_i^l$. Both p_i^l and q_i^l are obtained as a discretization of the predicted failure probability distribution $F_i(t)|d_i^0$ (Figure 6.3) (Dekker, Wildeman, and van Egmond 1996), with $p_i^l = R(t+\tau)/R(t)$ with $t = l \cdot \tau, l \in \mathbb{Z}^+$ and $R(t) = 1 - F_i(t)|d_i^0$.

For each individual component with current degradation d_i^0 and corresponding remaining useful life $F_i(t)|d_i^0$, an infinite-horizon age-based replacement policy is formulated to find the optimal maintenance time t_i^*. t_i^* represents the maintenance time at which the long-term mean maintenance cost per unit time (C_i^*) for component i with degradation d_i^0 on an infinite horizon is minimal. The determination of t_i^* is only possible for the next maintenance action on component i, as only for this maintenance action information on the current degradation d_i^0, and corresponding remaining useful life, is available. In other words, t_i^* is the short-term optimal maintenance time for component i.

As (6.7) relies on the well known renewal theory it is necessary to derive the failure probability distribution $F_i(t)|d_i^M$,which takes into account the imperfect maintenance actions, in order to derive the long-term optimal maintenance age $t_{i,l}^*$. d_i^M is defined as the distribution of the degradation level of component i at the start of a maintenance cycle (i.e. immediately after maintenance). The stochastic simulation procedure adopted to determine $F_i(t)|d_i^M$ is shown in Figure 6.3. Hence, the failure probability distribution $F_i(t)|d_i^M$ takes into account that the degradation level after maintenance depends on the degradation level before the maintenance action (i.e. imperfect maintenance) and the random failure threshold. Thus, $F_i(t)|d_i^M$ is the long-term failure probability distribution without considering any information on the current degradation level of components. By using $F_i(t)|d_i^M$ to determine $t_{i,l}^*$, (6.7) remains valid even with the introduction of imperfect maintenance and a random failure threshold. The long-term optimal maintenance age $t_{i,l}^*$, with corresponding cost $C_{i,l}^*$, is found by introducing the failure probability $F_i(t)|d_i^M$ (i.e $D_i(t_0) = d_i^M$) in (6.7) and (6.8). The long-term optimal maintenance age $t_{i,l}^*$ is used to schedule the m^{th} maintenance action $(m > 1)$ on component i, as for these maintenance actions no predictive information is yet available.

Consider m maintenance actions $(m \in \mathbb{Z}^+)$ are scheduled on component i within the planning horizon PH from the current time t_{cur} onwards, where t_{cur} includes the cumulative maintenance durations. Each time new information becomes available, the maintenance schedule is updated. The tentative maintenance schedule at t_{cur} for component i becomes (Figure 6.4):

$$T_{i,M}(m) = \begin{cases} t_{cur} + t_i^*, & \forall m = 1 \\ t_{cur} + t_i^* + \left(t_{i,l}^* + t_{i,p}\right) \cdot (m-1), & \forall m > 1 \end{cases} \qquad (6.9)$$

$$with \max\left(T_{i,M}\right) \leq PH$$

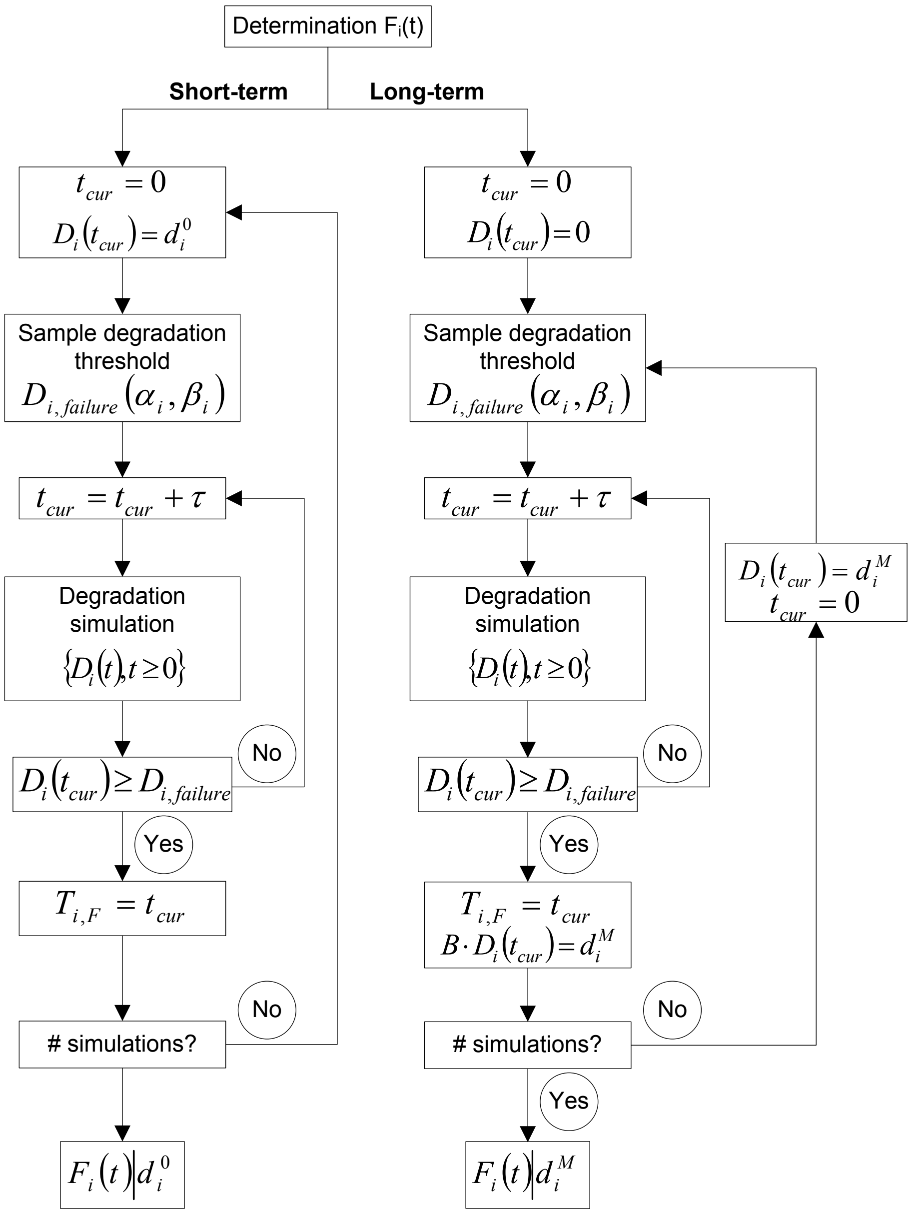

Figure 6.3: Simulation procedure for the determination of $F_i(t)$.

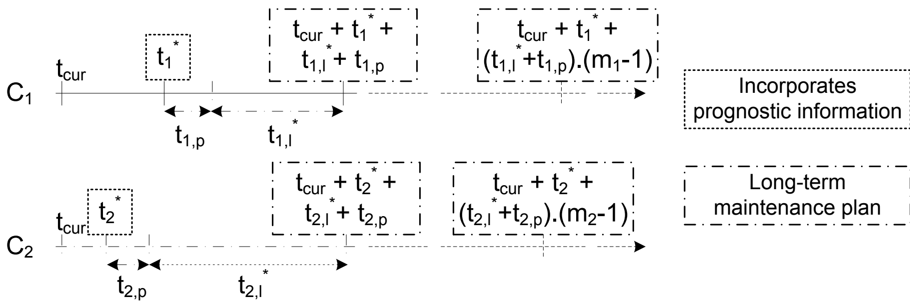

Figure 6.4: Example of a tentative maintenance schedule for a two-component system with optimal short-term maintenance time t_i^* based on predictive information and optimal long-term maintenance time $t_{i,l}^*$.

As mentioned by van der Duyn Schouten and Vanneste (1990): "Notice that (6.7) is in fact a discretized version of an age-replacement strategy, but as far as the lifetime distribution of the components is concerned knowledge of the sequence $(p_i^l)_{l=0}^{t-1}$ suffices. It is irrelevant whether the lifetimes themselves have a discrete or continuous probability distribution."

6.4.3 Penalty functions

Grouping maintenance actions results in shifting maintenance activities from their individual optimal maintenance time t_i^* or $t_{i,l}^*$, to the joint execution time $t_{G_j}^*$, which is defined as the optimal maintenance execution time of group G_j. There are two possibilities in shifting maintenance from their individual optimal times: the failure probability of some components will be increased by extending their useful life, while for others the useful life will be decreased. In order to define the effect of shifting maintenance actions from their optimal times, penalty functions are constructed. A penalty function h_i defines the expected additional cost of shifting the maintenance time from the optimal maintenance time t_i^* or $t_{i,l}^*$ for a component. Penalty functions for both the next optimal maintenance time t_i^*, based on the short-term information, as for the m^{th} ($m > 1$) maintenance occurrence, based on the long-term optimal maintenance time $t_{i,l}^*$, are defined. The penalty function, by adopting a long-term shift (Wildeman et al. 1997) with Δt the shift from the optimal maintenance time and defined as $\Delta t = z\tau, \forall z \in \mathbb{Z}$, for the first maintenance action on component i is defined as (Dekker, Wildeman, and van Egmond 1996):

$$h_i\left(t_i^*+\Delta t\right)=\left\{\begin{array}{ll}\sum\limits_{j=t_i^*}^{t_i^*+\Delta t-1}\left(q_i^j b_i|d_i^0-C_{i,l}^*\right)\prod\limits_{l=t_i^*}^{j-1} p_i^l|d_i^0, & \forall\Delta t\geq 0\\ \sum\limits_{j=t_i^*+\Delta t}^{t_i^*-1}\left(C_{i,l}^*-q_i^j b_i|d_i^0\right)\prod\limits_{l=t_i^*+\Delta t}^{j-1} p_i^l|d_i^0, & \forall\Delta t\leq 0\end{array}\right. \tag{6.10}$$

According to the long-term shift rule the execution interval of the first maintenance action is changed according to the predictive short-term information, while all future maintenance intervals remain $t_{i,l}^*$, the long-term optimal maintenance time (Figure 6.4). The penalty function for the m^{th} maintenance action, with $m>1$, on component i becomes:

$$h_i^m\left(t_{i,l}^*+\Delta t\right)=\left\{\begin{array}{ll}+\infty, & \forall\Delta t\leq e\\ \sum\limits_{j=t_{i,l}^*+\Delta t}^{t_{i,l}^*-1}\left(C_{i,l}^*-q_i^j b_i|d_i^M\right)\prod\limits_{l=t_{i,l}^*+\Delta t}^{j-1} p_i^l|d_i^M, & \forall e<\Delta t<0\\ 0, & \forall\Delta t=0\\ \sum\limits_{j=t_{i,l}^*}^{t_{i,l}^*+\Delta t-1}\left(q_i^j b_i|d_i^M-C_{i,l}^*\right)\prod\limits_{l=t_{i,l}^*}^{j-1} p_i^l|d_i^M, & \forall\Delta t\geq 1\end{array}\right. \tag{6.11}$$

with e the floor of $\left((m-1)\cdot t_{i,l}^*/\tau\right)$ (Bouvard et al. 2011). When a component i fails, the penalty function h_i of the failed component is defined as:

$$h_i\left(t_{i,F}\right)=\left\{\begin{array}{ll}0, & \forall t=0\\ +\infty, & \forall t>0\end{array}\right. \tag{6.12}$$

This means, when a component i fails, preventive maintenance actions on the other components can be performed during the downtime due to the failure of component i. Due to this assumption, opportunistic maintenance is thus included in the model.

6.4.4 Maintenance activities grouping

The aim is to group the maintenance activities on the planning horizon PH in order to minimize the maintenance cost on this planning horizon. The planning horizon PH is chosen in a way that both shifting maintenance forward and backwards in time is possible for the first maintenance action on each component

i. The reason for this is that the timing of the first maintenance action is crucial, as this is defined by the predictive information. Moreover, this definition of the planning horizon diminishes the finite horizon effect (Dekker, Wildeman, and van Egmond 1996). The finite planning horizon is defined as:

$$PH = \max_{i \in (1,\dots,n)} \left(\left(t_i^* + t_{i,l}^* + t_{i,p} \right), \varepsilon_i \right) \tag{6.13}$$

The parameter ε_i is defined as the prognostic horizon for component i. The prognostic horizon is the time between two consecutive predictions of remaining useful life of component i, based on newly available component degradation information. Each time the predictive information is updated; this information is used to schedule maintenance actions on the planning horizon PH. This means when ε_i is large, $PH = \varepsilon_i$. Hence, maintenance actions are planned and grouped for the entire prognostic horizon, as only within time ε_i new information on component degradation levels will be available to update the maintenance schedule. The prognostic horizon ε_i is assumed to be one time unit in this chapter (i.e. $\varepsilon_i = \tau$), unless stated otherwise.

Grouping of maintenance activities on PH can be done by using the defined penalty functions in (6.10), (6.11) and (6.12). Define $H_{G_j}\left(t_{G_j}\right)$ the group penalty cost function of group G_j when maintenance activities on components $i \in G_j$ are all performed at time t_{G_j} instead of their individual optimal times t_i^*. The optimal maintenance time $t_{G_j}^*$ of the group is derived by the following equation:

$$H_{G_j}\left(t_{G_j}^*\right) = H_{G_j}^* = \min_t \left(\sum_{i \in G_j} h_i(t) \right) \tag{6.14}$$

The savings Q_{G_j} by grouping maintenance operations $i \in G_j$ and executing them at time $t_{G_j}^*$ can be calculated as follows:

$$Q_{G_j}\left(t_{G_j}^*\right) = (|G_j| - 1) \times S - H_{G_j}^* \tag{6.15}$$

If the savings Q_{G_j} are positive, the group G_j is cost effective, which means it is better to group the maintenance actions rather than performing them at their optimal individual times t_i^*. The final objective is to find the grouping structure GS_k that minimizes the total maintenance cost on the planning horizon PH. An adapted version of the grouping algorithm developed by Wildeman et al. (1997) is used heuristically to find the optimal grouping structure GS_k. A constraint is added to this algorithm, as it is not allowed to group two maintenance actions on the same component (Bouvard et al. 2011). Moreover, the grouping algorithm of Wildeman et al. assumes that each component is to be preventively maintained only once in the planning horizon and maintenance durations are neglected. In order to develop the grouping algorithm to incorporate multiple maintenance actions on one component within the planning horizon and non-zero maintenance times, the model extensions proposed by (Do Van et al. 2011) are implemented for the predictive maintenance policy. Furthermore, this approach is extended by the inclusion of non-zero downtimes for corrective maintenance actions. Practically, this means that after each corrective maintenance action the maintenance planning and grouping is updated in order to incorporate the corrective maintenance duration $t_{i,c}$.

6.4.5 Maintenance execution and rolling-horizon update

Based on the previous step a maintenance schedule on the planning horizon PH is constructed. Maintenance actions are executed according to the maintenance schedule. A rolling-horizon approach is considered as each time the planning horizon is shifted and the maintenance schedule is updated by including newly available information on component degradation and the corresponding remaining useful life. This means that after each update of the rolling-horizon and component degradation, the procedure as described starts again (Figure 6.2). In this way a dynamic and adaptive predictive maintenance policy is developed, since it is based on the currently available predictive information deduced from the component degradation.

6.5 Component dependencies

When considering multi-component systems, three major categories of dependencies exist. These are stochastic, structural and economic dependence (Nicolai and Dekker 2007). These three types of dependencies are also considered in the constructed maintenance model.

6.5.1 Stochastic dependence

Stochastic dependence implies that a failure of one component possibly has an influence on the deterioration or state of other components in the system resulting in secondary damage or failure. The failure interaction described in this chapter builds on the type I failure interaction defined by Murthy and Nguyen (1985). Three different maintenance or replacement scenarios are considered when a component fails. In the first maintenance scenario only maintenance or replacement of the primary failed component is necessary (i.e. no secondary damage), in the second maintenance scenario maintenance of both primary failed component and one secondary damaged component is required, while in the third maintenance scenario maintenance of the whole subassembly is necessary due to secondary damage to several components. This implies that whenever more than one component is affected by the failure of another component, the entire system needs maintenance. All corrective maintenance scenarios are initiated by failure of one of the components. The corrective maintenance scenarios are sampled from a multinomial distribution:

$$f(x; n, p_i) = (n!/(x_1!, \ldots, x_k!))\,(p_1^{x_1}, \ldots, p_k^{x_k})\,, when \sum_{i=1}^{k} x_i = n \qquad (6.16)$$

where $x = (x_1, \ldots, x_k)$ gives the number of each of k outcomes in n trials of a process with fixed probabilities $p_i = (p_1, \ldots, p_k)$ of individual outcomes in any one trial. The vector p_i has non-negative integer components that sum to one. The vector p_i defines the probabilities of having a certain failure scenario at failure of component i ($p_c = (p_1 = 0.85, p_2 = 0.1, p_3 = 0.05)$). This means that for corrective maintenance 85% of the actions consist of only replacing the primary failed component, 10% consists of replacing both primary failed component and one secondary damaged component, and in 5% of the cases a replacement of the entire subassembly is necessary. When the number of components n is greater than two, p_2 can still be further subdivided over all n components in the system.

By including stochastic dependence into the maintenance model, two types of failures emerge: natural and induced failures. The natural failures are modeled by the degradation model described in Section 6.2.1, while the induced failures are described by the probabilities p_i in (6.16). In this way the corrective cost includes a part attributed to the repair of secondary damage. It is however possible to extend this approach as for a system with stochastic dependencies one can suppose that changes in the deterioration or operating condition of one component affects the degradation behavior of another component. In other words, failure of one component does not have to lead to a direct failure of another component, like modeled here; it can for example only affect the degradation rate of another component. The inclusion of this type of stochastic dependence into the proposed model is an opportunity for future research.

6.5.2 Economic and structural dependence

In order to be able to determine the performance of the proposed predictive maintenance policy when considering different levels of dependence (e.g. partial dependence) between the components, a dependence parameter α_d is introduced. This parameter α_d reflects the advantage of performing maintenance on multiple components at once compared to maintenance on a single component, in other words it affects the set-up cost S by adapting the savings Q_{G_j} (see (6.15)) when grouping maintenance as follows:

$$Q_{G_j}\left(t^*_{G_j}\right) = \alpha_d \times (|G_j| - 1) \times S - H^*_{G_j} \tag{6.17}$$

The dependence parameter α_d is assumed to incorporate the effect of both economic and structural dependence between the components in the considered system. This is the case because the set-up cost S contains a part regarding economic dependence (e.g. transportation cost, maintenance set-up cost) which is rather straightforward and also defined in (Nicolai and Dekker 2007). Another part regarding structural dependence is added to this set-up cost due to the inclusion of non-zero maintenance downtimes. For structural dependent components, the maintenance downtime and related costs can be decreased by performing maintenance simultaneously rather than individually, because all components have to be dismantled for maintenance anyway, independent on which component(s) need(s) maintenance (i.e. maintenance dependence (Nicolai and Dekker 2007)). The dependence parameter α_d ranges from 0 (0%) to 1 (100%), where $\alpha_d = 0$ means no economic and/or structural dependence, $\alpha_d = 1$ means maximal economic and/or structural dependence between the components and $0 < \alpha_d < 1$ corresponds to partial dependence. The set-up cost S_i, where t the preventive replacement time, for a preventive and corrective maintenance action respectively can thus be defined as:

$$S_i(t) = \begin{cases} S_{ED} + t_{i,p} \cdot C_d, & \forall t < T_{i,F} \\ S_{ED} + t_{i,c} \cdot C_d, & \forall t \geq T_{i,F} \end{cases} \tag{6.18}$$

where S_{ED} is the economic dependent set-up cost (e.g. transportation cost, maintenance set-up cost), $t_{i,p}$ is the downtime due to a preventive maintenance action and $t_{i,c}$ is the downtime caused by a corrective action. C_d is the cost per unit time of downtime due to unavailability of the system. Considering this definition of economic and structural dependence, the set-up cost S in (6.7) becomes:

$$S_i(t) = S_{ED} + t_{i,p} \cdot C_d + (t_{i,c} \cdot C_d - t_{i,p} \cdot C_d) \cdot \left(1 - \prod_{l=0}^{t-1} p_i^l\right) \tag{6.19}$$

6.6 Maintenance policies for comparison

In order to determine the performance of the developed dynamic predictive maintenance policy, it is compared to five other conventional maintenance policies. Moreover, not only the mutual comparison of the maintenance policies is interesting; it is also valuable to determine the performance of each policy for different levels of dependence within a multi-component system. The objective of all policies is to minimize the long-term mean cost per unit time, defined as C^*. The considered maintenance policies are:

- *Block-based maintenance*: a component i is maintained every $T_{b,i}$ time units, independent of the failure history of the component (Figure 6.5a) (Barlow and Proschan 1964). The optimal cost of the policy is defined as $C^*(T_{b,i})$.
- *Age-based maintenance without grouping*: under this policy, a unit is always maintained at its age $T_{a,i}$ or failure, whichever occurs first, where $T_{a,i}$ is a constant (Figure 6.5b) (Barlow and Proschan 1964). The optimal cost of the policy is defined as $C^*(T_{a,i})$.
- *Age-based maintenance with grouping*: under this policy, a unit is always replaced at its age $T_{a,i}$ or failure, whichever occurs first, where $T_{a,i}$ is a constant (Figure 6.5b) (Barlow and Proschan 1964), but the same grouping algorithm as in the described predictive maintenance policy is added. This maintenance policy is described by Dekker, Wildeman, and van Egmond (1996) and the optimal cost of the policy is defined as $C^*(T_{a,i})$.
- *Inspection condition-based maintenance*: a component i is inspected every T_{insp} time units and a degradation control-limit policy is applied. When the degradation at the time of inspection $D_i(T_{insp}) > TH_{P,i}$ preventive maintenance is performed, with $TH_{P,i}$ the preventive maintenance degradation threshold. When $D_i(t) > TH_{F,i}$ a corrective maintenance action is performed, with $TH_{F,i}$ the failure threshold $D_{i,failure}$ (Figure 6.5c). The optimal cost of the policy is defined as $C^*(T_{insp}, TH_{P,i})$.
- *Continuous condition-based maintenance*: component degradation is monitored continuously over time (i.e. every discrete time unit τ) and a degradation control-limit policy is applied. When the degradation $D_i(t) > TH_{P,i}$ preventive maintenance is performed, with $TH_{P,i}$ the

preventive maintenance degradation threshold. When $D_i(t) > TH_{F,i}$ a corrective maintenance action is performed, with $TH_{F,i}$ the failure threshold $D_{i,failure}$ (Figure 6.5d). The optimal cost of the policy is defined as $C^*(TH_{P,i})$.

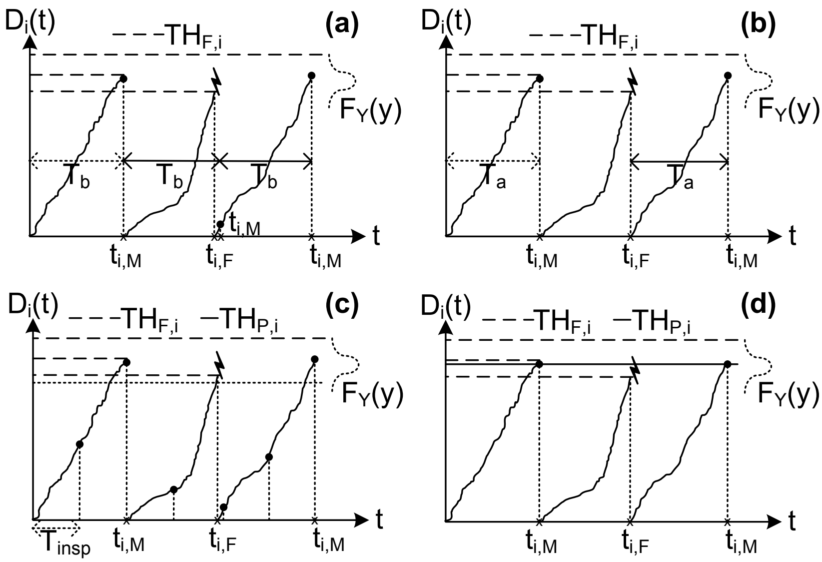

Figure 6.5: Maintenance policies for the performance comparison with the dynamic predictive maintenance policy. (a) Block-based maintenance policy. (b) Age-based maintenance policy (c) Inspection condition-based maintenance. (d) Continuous condition-based maintenance.

6.7 Numerical example

A numerical example is presented in order to validate the developed dynamic predictive maintenance policy and to compare its performance to several conventional maintenance policies (Section 6.6). Moreover, the sensitivity to the prognostic distance ε_i, dependence parameter α_d and imperfect maintenance parameter γ are quantified.

6.7.1 Input data

Consider a three component system ($n = 3$) with n non-identical components. The component degradation parameters, as described in detail in Section 6.2.1, are given in Table 6.1. In order to better understand the component degradation behavior, we discuss the parameters in detail. The time to failure of a component is characterized by three parameters (i.e. the degradation model, the random failure threshold and the imperfect maintenance). The parameters of the degradation model determine the expectation of the increase per unit time $E(D_i(t)) = \upsilon_i/\mu_i$. Furthermore, an increase in β_i reduces the variability of the random failure threshold, which results in a lower probability of early failures of a component. The parameters for imperfect maintenance are the same for all components. Based on the parameter definition like shown in Table 6.1, it can be concluded that component 1 has the longest time to failure.

Table 6.1: Component degradation parameters.

Component n	υ_i	μ_i	α_i	β_i	γ_i	δ_i
1	2,00	1	100	20	0,2	3
2	0,40	0,2	100	3	0,2	3
3	0,32	0,2	100	3	0,2	3

The corresponding cost and time parameters for all components are shown in Table 6.2. t_{wait} stands for the waiting time, $t_{replace}$ for the actual replacement time, t_{inst} for the installation time and the start-up time of the system and finally t_{secD} stands for the time to repair secondary damage. All these parameters determine the downtime due to preventive maintenance $t_{i,p}(t_{replace}, t_{inst})$ and corrective maintenance $t_{i,c}(t_{wait}, t_{replace}, t_{inst}, t_{secD})$. The cost of working (70€/h), cost of transportation (120€) and downtime cost rate (200€/h) are also considered in the numerical example. Imperfect maintenance is modeled by the improvement parameter B defined by its probability density distribution $f(b)$ which is modeled as a beta distribution with parameters γ (0.2) and δ (3). The dependence parameter α_d is assumed to be 0.25, unless stated otherwise. Time is discretized with a period τ equal to one and $\varepsilon_i = \tau = 1$ (i.e. continuous monitoring), unless stated otherwise.

6.7.2 Advantage of maintenance grouping and predictive information

For the given system the long-term mean maintenance cost per unit time is evaluated by stochastic simulation. Figure 6.6 shows several simulated paths of

Table 6.2: Cost and time parameters. Time parameters are modeled by a triangular distribution with parameters μ and σ.

$c_{i,p}$	$c_{i,c}$	t_{wait}		t_{repair}		t_{inst}		t_{secD}	
		μ	σ	μ	σ	μ	σ	μ	σ
605	5805	10	1	3	0,5	3	0,5	10	1
665	5865	10	1	3	0,5	3	0,5	10	1
475	5675	10	1	3	0,5	3	0,5	10	1

the mean maintenance cost per unit time for the dynamic predictive maintenance policy ($\varepsilon_i = 1$).

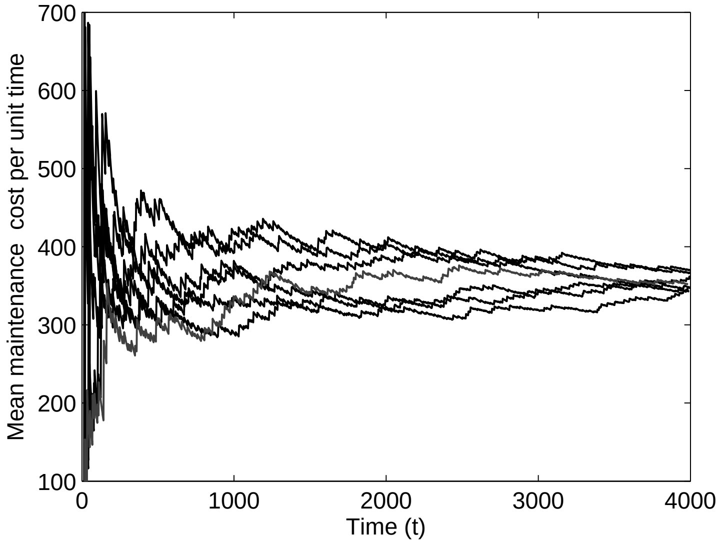

Figure 6.6: Maintenance cost per unit time for the dynamic predictive maintenance policy ($\varepsilon_i = 1$) for the described system.

The mean maintenance cost per unit time in relation to the prognostic horizon ε_i for the dynamic predictive maintenance policy is given in Figure 6.7. By comparing the performance of the predictive maintenance policy with an age-based policy without grouping and an age-based policy with grouping (Section 6.6), the advantage of grouping and using predictive information in maintenance scheduling for multi-component systems becomes clear. The dynamic predictive maintenance policy takes advantage of the available predictive information to dynamically group and schedule maintenance activities. The influence of the prognostic horizon ε_i on the long-term mean maintenance cost per unit time for the dynamic predictive maintenance policy is as to be expected. As the prognostic horizon ε_i becomes larger (i.e. the system degradation is inspected less frequently) the gain by incorporating the predictive information in maintenance scheduling becomes smaller, and eventually turns out to be negligible. This is due to the fact that when the prognostic horizon ε_i becomes larger it is more difficult or even impossible to accurately follow the component deterioration. The smaller the prognostic horizon ε_i, the more information there is available for dynamically adapting the maintenance schedule according to the real component deterioration, which results in higher cost savings. Note that we do not take a monitoring cost into account in the developed cost functions; it is however straightforward to implement this (i.e. a fixed monitoring cost per unit time can be added to the results). The difference in cost without inclusion of the monitoring cost in fact reflects the maximal investment in monitoring devices one can make such that the predictive maintenance policy remains optimal. Based on the monitoring cost and the results of Figure 6.7 it is possible to determine the optimal prognostic horizon ε_i for monitoring the system.

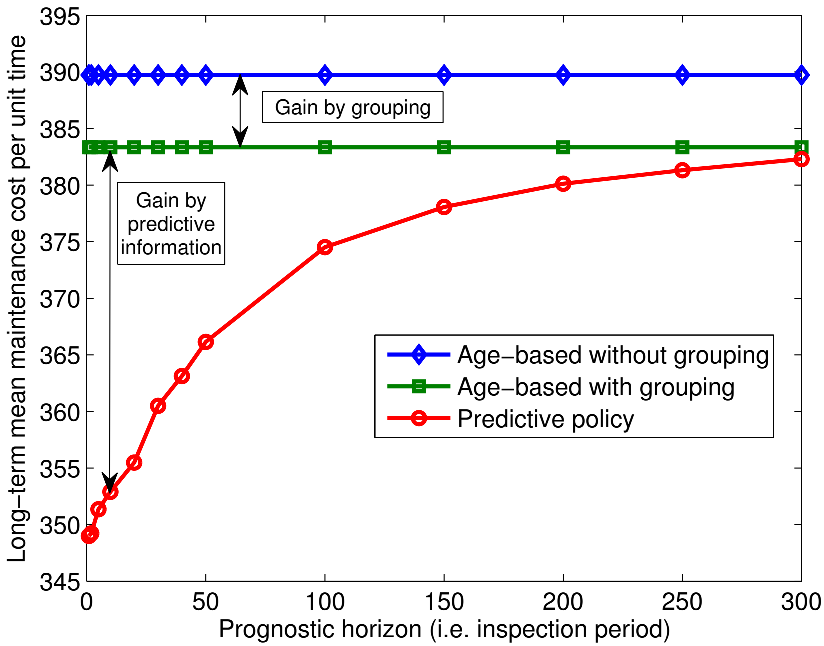

Figure 6.7: Influence of the prognostic horizon ε_i (i.e. inspection period), with $\alpha_d = 25\%$, on the long-term mean maintenance cost per unit time.

6.7.3 Does prognosis extend the component lifetime?

Condition-based and predictive maintenance are generally perceived in literature and industry as component lifetime extending maintenance policies. However, few studies investigate the effect of a maintenance policy on the lifetime of the components. In this chapter the component lifetimes in an age-based policy without grouping is used as a baseline for a comparison to the component lifetimes in two other maintenance policies. These two policies are the age-based policy with grouping and the dynamic predictive maintenance policy. From Table 6.3 it can be seen that the age-based preventive maintenance policy with grouping generally decreases the component lifetime until maintenance. Still, based on the cost criterion this policy outperforms the baseline policy (Figure 6.7), as maintenance is cheaper when grouped ($\alpha_d = 0.25$). This means that the age-based policy with grouping sacrifices component useful life in order to perform cheaper grouped maintenance. The predictive maintenance policy is based on the same grouping algorithm as the age-based policy with grouping. However, from Table 6.3 it is clear that the predictive maintenance policy uses the predictive information on top of the grouping algorithm to dynamically and adaptively schedule maintenance actions. This shows in the results by an increase in component lifetime compared to both other maintenance policies. The gain by predictive information, like shown in Figure 6.7, can thus be explained by this increase in component lifetime. Thus, the predictive maintenance policy uses both information on the system structure (i.e. component dependencies) and component degradation to optimally schedule maintenance activities. These findings in fact validate the results discussed in Section 6.7.2.

6.7.4 Maintenance policy performance in relation to dependence α_d

The maintenance policies described in Section 6.6 are optimized with regard to the long-term mean maintenance cost per unit time in order to make comparison with the developed predictive maintenance policy possible. Moreover, the influence of the dependence parameter α_d on each optimal policy is investigated by varying α_d from 0 (0%) to 1 (100%). The parameter values with regard to the optimal policies can be found in Tables 6.4 - 6.9, while the influence of the dependence parameter α_d on the long-term mean maintenance cost per unit time for all considered maintenance policies (Section 6.6) and the dynamic predictive maintenance policy is shown Figure 6.8.

Looking first at the optimal maintenance policies individually; it is clear that when $\alpha_d = 0\%$ a component individual optimal policy is also the optimal policy for the entire system, as no dependencies exist and the problem can be

Table 6.3: Mean total number of preventive and corrective maintenance actions for the three components (C1, C2 and C3) of the considered system in a time horizon of 4000 time units with the age-based maintenance policy without grouping as the baseline ($\alpha_d = 0.25$).

	Age-based preventive maintenance without grouping			Age-based preventive maintenance with grouping			Predictive maintenance		
	C1	C2	C3	C1	C2	C3	C1	C2	C3
# preventive actions	88,09	131,59	109,40	91,89	130,26	122,10	89,06	130,48	107,95
# corrective actions	9,30	24,35	18,18	9,65	25,38	18,20	4,06	22,55	17,66
Total maintenance actions	97,39	155,94	127,58	101,54	155,64	140,30	93,13	153,03	125,61
Lifetime extension (%)				-4,09	0,19	-9,07	4,58	1,90	1,56

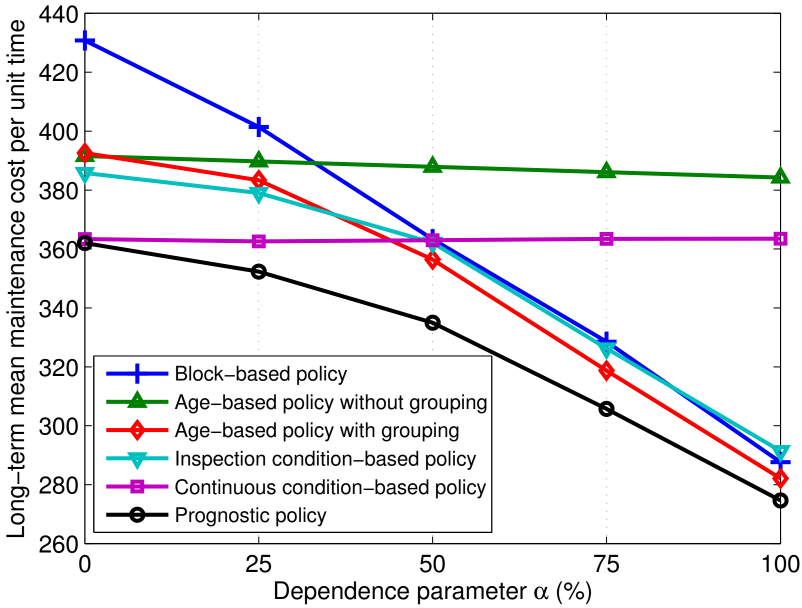

Figure 6.8: Influence of the dependence parameter α_d on the long-term mean maintenance cost per unit time for all considered maintenance policies (Section 6.6) and the dynamic predictive maintenance policy.

decomposed in n single-component optimization problems. However, when α_d is increasing the optimal system policy deviates from the component individual optimal policy. These and other conclusions that can be drawn for each maintenance policy from the analysis (Figure 6.8) are:

- *Block-based maintenance*: the optimal policy is changing with increasing dependence α_d. From $\alpha_d = 25\%$ it becomes cheaper to group all maintenance activities at one moment in time. As α_d increases up until 100%, the maintenance intervals $T_{b,i}$ are decreasing (Table 6.4) as it becomes cheaper to perform preventive maintenance (i.e. more savings when grouping maintenance), due to the higher dependencies between the components. The optimal block-based maintenance policy reduces to a group-based maintenance policy, which takes advantage of grouping maintenance actions, from the moment α_d reaches 25%. The block-based policy in fact allows a coordination of maintenance, but it has the disadvantage that it does not react to opportunities like for example failure of a component.

- *Age-based maintenance without grouping*: the optimal policy is not changing with α_d (Table 6.5). This is due to the impossibility to adjust a regular age-based policy for grouping maintenance activities, in contrast to for example a block-based maintenance policy. When α_d is small, the flexibility of the age-based policy results in lower costs compared to a block-based policy, however, when α_d is large the block-based policy performs better due to the possibility of maintenance coordination.

- *Age-based maintenance with grouping*: Dekker, Wildeman, and van Egmond (1996) introduced an age-based maintenance policy with grouping in order to tackle the problem of maintenance grouping within an age-based maintenance policy. The optimal parameters $T_{a,i}$ (Table 6.6) are the same as for a conventional age-based policy as the decomposition approach (i.e. individual component optimization) is used to develop an initial maintenance schedule. When α_d increases, it is clear that this policy outperforms the regular age-based and block-based policies. In fact the policy combines the flexibility of an age-based policy with the possibility of coordinating maintenance activities through the maintenance grouping algorithm.

- *Inspection condition-based maintenance*: the inspection frequency (with $T_{insp} \geq 5$) and preventive maintenance degradation thresholds $TH_{P,i}$ are decreasing as α_d is increasing (Table 6.7). The reason for this is that by decreasing T_{insp} and $TH_{P,i}$ the probability of having grouped maintenance is increasing. This phenomenon is even so strong for high numbers of α_d ($\alpha_d > 75\%$) that the inspection condition-based maintenance policy reduces to a block-based maintenance policy (i.e. group maintenance) in order to always group maintenance activities. This also means that from $\alpha_d > 75\%$ onward, the value of the information on the component deterioration becomes negligible.

- *Continuous condition-based maintenance*: as could be foreseen the continuous condition-based maintenance policy performs very well when no or low dependencies are present between components. This is the case because the real degradation of each component is monitored separately. However, when this degradation reaches the control limit, maintenance is performed regardless the state of the other components. This is the reason why the cost of this policy stays the same regardless the dependencies between components (Table 6.8). For systems with little interdependencies ($\alpha_d < 40\%$) this policy outperforms the other policies due to the use of condition monitoring information to schedule maintenance activities. The policy is however not capable to coordinate and group maintenance activities, which results in higher costs for systems with many interdependencies ($\alpha_d > 40\%$). It is interesting to see that the condition-based maintenance policy does not perform well for systems with highly interdependent components. For these systems it is thus certainly not optimal to use a condition-based control limit type policy, as maintenance is never coordinated and grouped.

In general it can be concluded that maintenance policies considering periodic maintenance or inspections (i.e. block-based and inspection condition-based maintenance policy) outperform maintenance policies with continuous review policies (i.e. age-based and continuous condition-based maintenance policy) for systems with highly dependent components. While the inverse is true for systems with little dependence between components. However, when combining the advantages of both types of policies (i.e. maintenance grouping and flexibility), as in the age-based policy with grouping proposed by Dekker, Wildeman, and van Egmond (1996), additional cost savings can be made for multi-component dependent systems.

Table 6.4: Optimal parameters for the block-based preventive maintenance policy.

Block-based preventive maintenance							
α_d (%)	$T_{b,1}$	$T_{b,2}$	$T_{b,3}$	C^*	D^*	$\sigma(C^*)$	$\sigma(D^*)$
0	33	23	29	430,79	0,0384	19,64	0,0016
25	29	29	29	401,44	0,0346	21,83	0,0018
50	26	26	26	363,31	0,0302	19,45	0,0016
75	26	26	26	328,51	0,0259	18,29	0,0015
100	23	23	23	287,61	0,0208	19,20	0,0016

Table 6.5: Optimal parameters for the age-based preventive maintenance policy without grouping.

Age-based preventive maintenance without grouping							
α_d (%)	$T_{a,1}$	$T_{a,2}$	$T_{a,3}$	C^*	D^*	$\sigma(C^*)$	$\sigma(D^*)$
0	37	24	29	391,54	0,0346	20,98	0,0017
25	37	24	29	389,74	0,0344	20,89	0,0017
50	37	24	29	387,91	0,0342	20,79	0,0017
75	37	24	29	386,09	0,0340	20,69	0,0017
100	37	24	29	384,26	0,0337	20,61	0,0016

Considering the performance of the presented dynamic predictive maintenance policy it can be concluded that it performs at least as good as or outperforms, dependent on the dependencies between the components, the other described maintenance policies (Figure 6.8 and Table 6.9). The reason for this is that the predictive maintenance policy dynamically updates the maintenance schedule

Table 6.6: Optimal parameters for the age-based preventive maintenance policy with grouping.

Age-based preventive maintenance with grouping							
α_d (%)	$T_{a,1}$	$T_{a,2}$	$T_{a,3}$	C^*	D^*	$\sigma(C^*)$	$\sigma(D^*)$
0	37	24	29	392,60	0,0347	20,56	0,0017
25	37	24	29	383,34	0,0332	19,77	0,0016
50	37	24	29	356,39	0,0301	18,28	0,0015
75	37	24	29	318,70	0,0253	22,81	0,0019
100	37	24	29	282,12	0,0208	17,75	0,0014

based on the real component deterioration and component interdependencies (Table 6.10 and 6.11). When $\alpha_d = 0\%$ the long-term mean maintenance cost per unit time is comparable to that of the continuous condition-based maintenance policy. This is logical as both policies consider the real component deterioration to schedule maintenance activities, while it is irrelevant to group maintenance activities when there is no component interdependence. This of course changes as α_d increases and component interdependencies come into play, which results in major cost savings when implementing the predictive maintenance policy compared to the continuous condition-based maintenance policy. When α_d increases to 100% the cost savings of the predictive maintenance policy compared to the maintenance policies considering coordinated or grouped maintenance (i.e. block-based policy, inspection condition-based policy and age-based policy with grouping) diminishes. This is the case because the added value of the predictive information is decreasing, because preventive group-based maintenance becomes cheaper. This means that not the real component deterioration is the major reason to schedule maintenance, but the cost savings due to grouping maintenance activities get the upper hand in determining when to schedule maintenance.

It can be concluded that the developed dynamic predictive maintenance policy leads to cost savings for multi-component systems with no dependence over partial dependence to full dependence due to its dynamic and adaptive nature. On the one hand, it considers the real component degradation by continuously (i.e. each discrete time unit τ) updating the remaining useful life of the components (i.e. prognostics); while on the other hand it takes into account the possible advantage of grouping maintenance activities due to the dependencies in the system. By doing so, the dynamic predictive maintenance policy is able to react to different degradation patterns and dependencies between components while always guaranteeing an optimal policy.

Table 6.7: Optimal parameters for the inspection condition-based maintenance policy.

Inspection condition-based maintenance										
α_d (%)	$T_{insp,1}$	$T_{insp,2}$	$T_{insp,3}$	$TH_{p,1}$	$TH_{p,2}$	$TH_{p,3}$	C^*	D^*	$\sigma(C^*)$	$\sigma(D^*)$
0	5	5	5	66	44	37	385,81	0,0345	18,57	0,0015
25	7	7	7	66	44	37	379,00	0,0338	16,86	0,0014
50	12	12	12	60	40	34	362,12	0,0324	20,84	0,0017
75	26	26	26	0	0	0	326,23	0,0274	20,70	0,0017
100	23	23	23	0	0	0	291,41	0,0212	17,20	0,0014

Table 6.8: Optimal parameters for the continuous condition-based maintenance policy.

Continuous condition-based maintenance							
α_d (%)	$TH_{p,1}$	$TH_{p,2}$	$TH_{p,3}$	C^*	D^*	$\sigma(C^*)$	$\sigma(D^*)$
0	75	53	46	363,39	0,0324	17,46	0,0014
25	75	53	46	362,55	0,0324	18,85	0,0015
50	75	53	46	362,95	0,0325	16,83	0,0014
75	75	53	46	363,44	0,0326	16,10	0,0013
100	75	53	46	363,50	0,0326	16,04	0,0013

Table 6.9: Optimal parameters for the dynamic predictive maintenance policy.

Dynamic predictive maintenance				
α_d (%)	C^*	D^*	$\sigma(C^*)$	$\sigma(D^*)$
0	358,69	0,0319	18,04	0,0015
25	348,99	0,0306	17,81	0,0014
50	331,70	0,0282	19,28	0,0015
75	302,40	0,0246	16,07	0,0013
100	271,31	0,0207	16,95	0,0014

Table 6.10: Maintenance timing for all three components during the first 160 time units for dependence parameter $\alpha_d = 0\%$.

Component n	Maintenance timing										
	36	38	48	63	68	89	96	100	114	125	138	160
1			x					x			x	
2		x		x		x			x			x
3	x				x		x			x		

Table 6.11: Maintenance timing for all three components during the first 160 time units for dependence parameter $\alpha_d = 100\%$.

Component n	Maintenance timing					
	19	49	61	90	123	158
1		x		x	x	x
2	x	x		x	x	x
3	x	x	x	x	x	x

6.7.5 Imperfect maintenance

The percentage improvement in mean maintenance cost per unit time of the dynamic predictive policy compared to three other maintenance policies, for different values of the imperfect maintenance parameter γ and $\alpha_d = 25\%$, is depicted in Figure 6.10. An increasing γ corresponds to more imperfect maintenance actions (i.e. maintenance quality decreases), reflected by a smaller mean and higher variability of the reduction in component degradation (Figure 6.9). The results in Figure 6.10 again show the capability of the predictive maintenance policy to adaptively react to changing component deterioration patterns implicitly caused by the maintenance quality. As a result the improvement in cost of the predictive maintenance policy gets bigger compared to the other policies, as the maintenance gets worse (γ increases). The reason for this is that the predictive maintenance policy uses information on component deterioration, also immediately after maintenance which in fact shows how "good" or "bad" the performed maintenance action is, to schedule maintenance activities. The increase in improvement is larger for the comparison with an age-based policy than with a block-based policy as γ increases. The reason for this is that a block-based optimal policy (i.e. all components are simultaneously maintained (Table 6.4)) is more conservative than an age-based optimal policy (Tables 6.5 and 6.6). This makes the age-based policies more sensitive to changes in the maintenance quality, which results in a faster decrease of performance as γ increases.

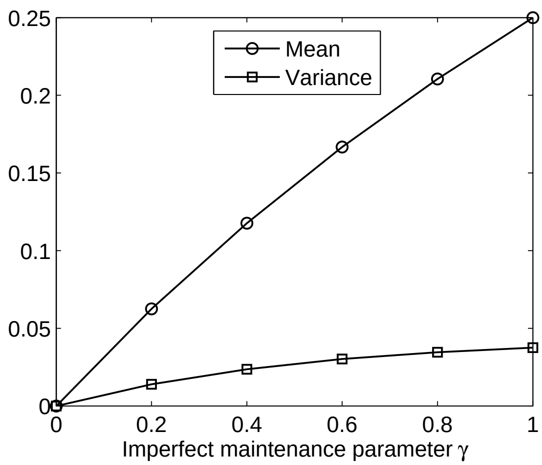

Figure 6.9: Mean and variance of improvement factor B in function of the imperfect maintenance parameter γ.

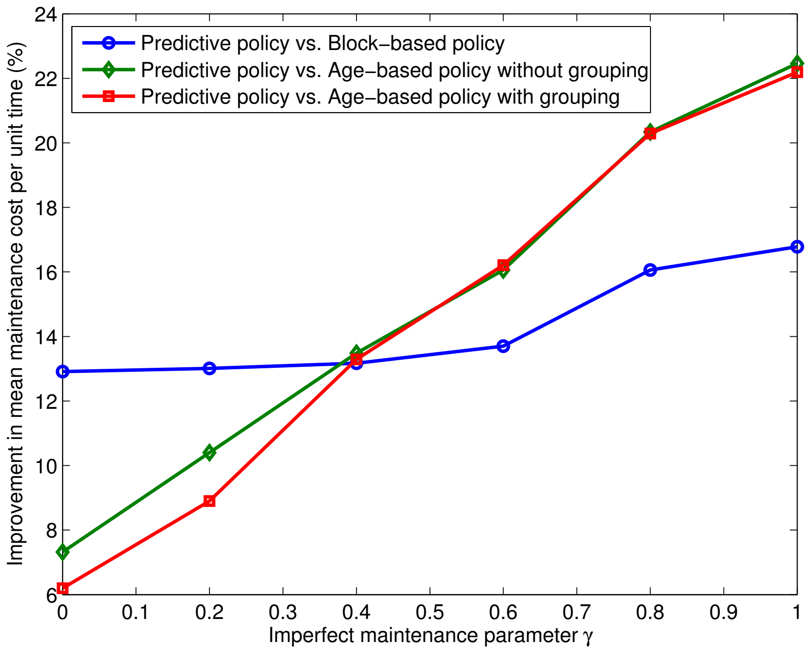

Figure 6.10: Improvement in mean maintenance cost per unit time for $\alpha_d = 25\%$ of the predictive maintenance policy compared to (1) the block-based policy, (2) the age-based policy without grouping and (3) the age-based policy with grouping for different values of the imperfect maintenance parameter γ.

6.8 Conclusions

The objective of this chapter was to provide an answer to the second research question of this dissertation. Consequently, this chapter presents a dynamic predictive maintenance policy (PdM) for complex multi-component systems that minimizes the long-term mean maintenance cost per unit time, while considering different component dependencies (i.e. economic, structural and stochastic dependence), that can be used for both long-term performance evaluation of PdM, as for real-time and dynamic maintenance decision making. Complex systems are considered as several extensions to previously published research are discussed. The inclusion of non-zero maintenance downtimes, imperfect maintenance and all types of component dependence (i.e. economic, structural and stochastic dependence) are the most important advancements on the state-of-the-art of multi-component maintenance scheduling. Moreover, predictive information is dynamically included into the presented maintenance policy in order to schedule maintenance in an optimal way. The maintenance schedule is updated when new (short-term) information on the degradation (e.g. by inspection) and remaining useful life of components becomes available. Furthermore, all component dependencies are considered to optimally group and schedule maintenance activities.

In order to determine and validate the performance of the presented dynamic predictive maintenance policy a numerical example is presented and it is extensively compared to five other conventional maintenance policies. These maintenance policies are: block-based maintenance, age-based maintenance, age-based maintenance with grouping, inspection condition-based maintenance and continuous condition-based maintenance. All policies are compared based on the objective of minimal mean maintenance cost per unit time, while considering different component dependencies (i.e. influence of dependence parameter α_d on the optimal policy). By including the dependence parameter α_d, the impact of partial dependence on the optimal policy is investigated. To our knowledge this is the first time that partial dependence is considered in multi-component system maintenance policies, as in previous studies the dependence is assumed to exist or not. Furthermore, the effect of the dynamic predictive maintenance policy on the component lifetimes, the effect of imperfect maintenance and the added value of predictive information in maintenance decision making are quantified. The results show significant cost savings for the presented dynamic predictive maintenance policy, as the policy is able to dynamically react to changing component deterioration and dependencies within multi-component systems. Furthermore, the magnitude of these savings depends on the component interactions present in the system, which clearly illustrates the importance to include these interactions in the maintenance decision problem. By doing so, the dynamic predictive maintenance policy assures an optimal maintenance policy all of the time rather than only over time.

Several directions for future work can be derived. Investigating system dependencies in addition to the discussed component dependencies is an interesting avenue for further research. The presented approach can be extended from a single-system multi-component level to a multi-system, multi-component level. An initial contribution in this direction has already been presented by Van Horenbeek et al. (2012). Different methods to model stochastic dependence and imperfect maintenance can be studied. Finally, other possibilities for future work can be found in the inclusion of inventory management or production schedules into the model. The extension of the predictive maintenance policy by the inclusion of inventory management is presented in Chapter 7 of this dissertation.

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Chapter 7

Joint maintenance and inventory policies

Some authors advocate that, when dealing with maintenance problems in a restricted way (i.e. not considering the spare parts availability), the results may be questionable because, in practice, the proposed policy cannot be adopted due to a lack of spare parts in inventory (Kaio, Dohi, et al. 2002). In fact, the availability of the spare-parts is one of the most important factors to avoid long downtimes of equipment (Diaz and Fu 1997). Therefore, the joint optimization of the maintenance and inventory problem is regarded as a promising area for the development of maintenance optimization (Van Horenbeek, Buré, et al. 2013; Sarker and Haque 2000). For a thorough study of integrated policies of maintenance and inventory, see for example (Guide and Srivastava 1997; Kabir and Al-Olayan 1996; Kennedy et al. 2002; Van Horenbeek, Buré, et al. 2013). Moreover, it is generally perceived that the introduction of predictive maintenance not only adds value to maintenance operations, but also to other elements within the value chain of a company. Predictive maintenance is often described as value adding for inventory management due to the better predictability of spare parts demand, which reduces stock outs and holding costs. However, no hard proof or detailed quantification on this statement

This chapter is based on A. Van Horenbeek, J. Buré, et al. (2013). "Joint maintenance and inventory optimization systems: a review". In: *International Journal of Production Economics* 143, pp. 499–508 and A. Van Horenbeek et al. (2013a). "On the use of predictive information in a joint maintenance and inventory policy". In: *Proceedings of the European Safety and Reliability Conference: ESREL* and A. Van Horenbeek et al. (2013b). "The effect of maintenance quality on spare parts inventory for a fleet of assets". In: *Reliability, IEEE Transactions on* 62.3, pp. 596–607 exists within the available literature. Therefore, this chapter investigates joint maintenance and inventory policies, with focus on how the use of predictive maintenance influences inventory decisions. Hence, the third research question is addressed, which is formulated as follows:

> "*How and how much value will predictive maintenance generate in the entire value chain, specifically looking to inventory management?*"

The chapter is subdivided into three main parts as follows. First a literature overview on joint maintenance and inventory models is presented (Section 7.1). Based on this literature review major directions for further research are derived, whereof two are addressed in the remainder of this chapter. These are defined as (i) the incorporation of predictive information in joint maintenance and inventory models and (ii) investigation of the effect of maintenance quality on a joint policy. The added value of predictive information in joint maintenance and inventory management is quantified by incorporation of an inventory policy into the predictive maintenance model presented in Chapter 6 (Section 7.2). As such a joint predictive maintenance and inventory policy for multi-component systems is developed. Finally, the effect of maintenance quality on a joint preventive maintenance and spare part inventory policy for a fleet of assets is investigated (Section 7.3).

7.1 Literature review on joint maintenance and inventory models

During the past decades, several joint maintenance and inventory optimization systems have been studied in literature. Compared to the sequential optimization of both models, Kabir and Al-Olayan (1996) reported a remarkable influence on total cost due to their joint optimization method. The review presented in this chapter focuses on models that include cost and optimization parameters related to both maintenance and inventory. The purpose of this section is to review the pertinent literature on joint maintenance and inventory optimization models for non-repairable parts and suggest possible gaps. A classification based on the following seven sets of criteria is made: inventory policies, maintenance characteristics, delays, multi-echelon networks, single-unit versus multi-unit systems, objective function and optimization techniques.

The main reason a company keeps an inventory of spare parts is to perform maintenance in order to restore the system in such a way that it can perform its intended function. The number of spare parts in inventory is determined by the demand, caused by corrective as well as preventive maintenance, for each spare part. Maintenance relies on the availability of spare parts in order to reduce failure downtime and costs. It is clear that maintenance and inventory management are strongly interconnected and should both be considered simultaneously when optimizing a company's operations. During the past decades, several joint maintenance and inventory optimization systems have been studied in literature. Compared to the sequential optimization of both models, Kabir and Al-Olayan (1996) reported a remarkable improvement on total cost due to their joint optimization method. Several reasons can be found for this cost reduction. On the one hand, maintenance models often rely on the assumption of an inexhaustible number of available spare parts (e.g. Barlow and Hunter (1960)) and on the assumption that these are available without any lead time (Dohi et al. 1998). These assumptions are not always realistic and it would be too expensive for a company to sustain such a system. On the other hand, the unilateral focus on the inventory policy might result in higher costs for maintenance (Acharya et al. 1986). The joint optimization of spare parts and maintenance takes into account the trade-off between maintenance and inventory policies.

As a precursor to mathematical models dedicated to maintenance problems, Barlow and Proschan (1965) contributed to the foundation of the development of maintenance and inventory models. Other early papers have an essential role on the consolidation of simultaneous optimization of inventory and maintenance policies (Falkner 1968; Kaio and Osaki 1978; Thomas and Osaki 1978). The development of integrated models of maintenance and inventory has two main sources. In the first source, original production inventory models, in order to improve their practical results, consider the fact that machines may fail. These are the integrated maintenance and inventory models whose source is the production inventory context. Imperfect production process is the term used to describe the original production inventory problem, where the production process is not perfect (e.g. the machine is subject to failure). According to Widyadana and Wee (2011), many researchers have extended the production inventory problem with machine breakdown models by considering other problems in production such as deterioration, preventive maintenance, and rework (Kennedy et al. 2002; Suliman and Jawad 2012). In fact, some authors criticized the naivety of most economic manufacturing quantity (EQM) models that consider production systems free from defects, deterioration, and failure (El-Ferik 2008). For this reason, the list of papers that deal with imperfect production processes is very long (S. Chen and Chang 2008; Dhouib et al. 2012; C. Lin et al. 2003; G. Lin and Gong 2006; Y. Lin et al. 2011; Widyadana and Wee 2011).

The second source for the development of integrated models is the maintenance context (i.e. based on classical maintenance models). Maintenance models may be improved by linking the inventory problem to the original maintenance problem without the assumption of an infinite supply of spare parts. In this chapter, we will build further on this type of model. Focus is on papers that include costs (e.g. inventory and maintenance costs) and optimization parameters (e.g. ordering time, replacement time, etc.) related to both maintenance and inventory management. As far as the author is aware, this is the first review on joint maintenance and inventory optimization taking into account both the costs and parameters related to maintenance and inventory. Another interesting review paper on the joint optimization of maintenance and inventory policies was written by Dohi et al. (1998), but in the end only inventory related costs were included in the models reviewed in their paper. Searching Web of Science and Google Scholar using the key words 'maintenance', 'inventory', 'replacement' 'joint' and 'ordering' gave us the majority of the papers. The other papers were found by scanning the references and using the 'cited by' option. The scope of the review is limited to models for non-repairables. If a non-repairable part breaks down, it is removed and replaced by a new part. The reader interested in models for repairable spares is referred to e.g. Y. T. Park and K. S. Park (1986); J. Sarkar and S. Sarkar (2001) and de Smidt-Destombes et al. (2009). The purpose of this section is to review the pertinent literature on joint maintenance and inventory models for non-repairables and to suggest possible gaps that could lead to interesting future work. A classification based on the following seven sets of criteria was made: inventory policies, maintenance characteristics, delays, multi-echelon networks, single-unit versus multi-unit systems, objective function and optimization techniques.

7.1.1 Characteristics of joint maintenance and inventory optimization models

In order to detect gaps in the existing literature on joint maintenance and inventory models, a framework is constructed first that classifies all characteristics which are of importance when considering these models. The framework is depicted in Figure 7.1. The literature discussed in Section 7.1.2 of this chapter is classified according to the defined characteristics in the framework of Figure 7.1. Based on this classification it is possible to determine which research has been done and still has to be done on joint maintenance and inventory models. In this way, directions for further research are derived, whereof some are handled in the remainder of this chapter.

Inventory characteristics

Inventory can be reviewed continuously or periodically and both approaches have been used in joint systems (see Table 7.2, column I). In the continuous

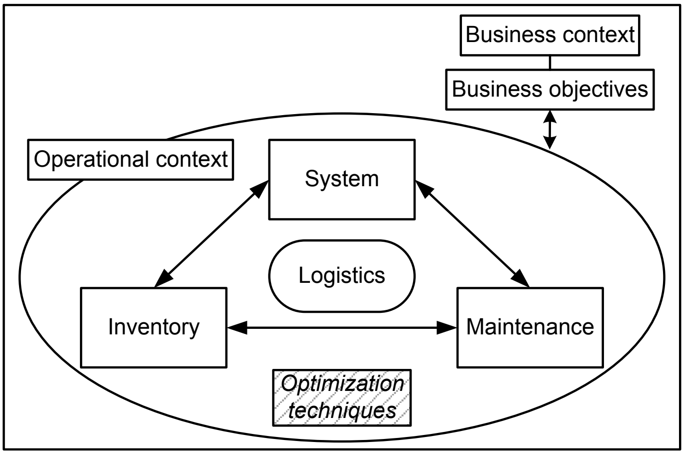


Figure 7.1: Framework for joint maintenance and inventory optimization models.

review policy, the inventory levels are checked continuously and when a certain condition is met (e.g. the number of spare parts drops below a certain level), spares are ordered. Two well-known and often used continuous review policies are the (s, S) and the (s, Q) policy. Using an (s, S) policy, one orders spares to reach the order-up-to level S, whenever the inventory level drops below s. When Q units are ordered each time inventory drops below s, it is called an (s, Q) policy. When there is a per unit demand, both systems give the same result if Q equals S minus s. A special case of a continuous (s, Q) review policy, which is mainly used for low cost and high demand spare parts, is a two-bin policy where a replenishment order is placed when the first bin is empty. At that time, one starts to use the second bin and a new bin is ordered.

In a periodic review policy, at the beginning of each cycle, spares are ordered depending on e.g. the forecasted demand of the next period. As an example, let R be the length of the review interval. Using the (R, S) policy, one orders up to S units each time at the beginning of the review interval. Another important inventory characteristic to take into account is the consideration of a single-unit or multi-unit inventory. When failure frequencies are high or lead times are very long, it might be interesting to keep more than one part in stock, even though a single unit system is under consideration. On the other hand, keeping multiple units in inventory increases the risk of obsolescence. Obsolescence is a major (cost) issue for spare parts which are rarely needed for replacement (Kennedy et al. 2002).

Maintenance characteristics

The degrees of maintenance Different degrees of maintenance are discussed in the literature (Pham and H. Wang 1996) (also see Section 2.2.4). When the fixed system is as good as new after the maintenance actions, it is called a perfect repair. Unfortunately, most repairs do not fix the system perfectly. A minimal repair restores the system to an as bad as old state, which means that the system has the same failure rate after repair as it had just before the repair. Imperfect repair restores the system to a state somewhere in between as good as new and as bad as old. A less favorable degree of repair is worse repair in which the systems condition is worse than just before failure. In some circumstances one might even have a worst repair, which means that the system breaks down completely after maintenance.

The reason to consider the degrees of maintenance even for non-repairable parts, as considered in this chapter, is that a replacement of a part by a new part can be imperfect too. Wrong installation of the part, outlining errors etc. can result in imperfect replacement. Moreover, when considering multi-unit systems, the replacement of one broken unit does not always make the entire system perfect again. A simple example is a bicycle wheel, where the entire wheel is seen as a system that consists of multiple non-repairable units, the spokes. When one spoke breaks, the replacement of it does not result in an as good as new system or wheel; it results in an imperfect repair of the system. Armstrong and Atkins (1998) make a distinction between a major and a minor failure and Nguyen and Bagajewicz (2010) assume imperfect preventive maintenance. All other papers considered in this review assume that the systems are perfectly maintained or do not mention any assumption concerning the degree of restoration.

Maintenance policies Three major maintenance policies can be distinguished (Section 1.3 and 2.2.2). The most reactive policy is failure-based maintenance (FBM) (also called corrective maintenance). Whenever a failure occurs, the units are replaced or repaired as soon as possible. If no spare part is available, the maintenance is delayed and possibly high downtimes are induced. A second well known policy is preventive maintenance. Several policies might be classified as being preventive. A review is provided by H. Wang (2002) and a brief explanation of the most important preventive maintenance policies for non-repairables, considering both single-unit and multi-unit systems, is provided. For single-unit systems these policies are:

- Age-based preventive maintenance: a unit is always replaced at its age T or failure, whichever occurs first, where T is a constant (Barlow and Hunter 1960).

- Block-based or periodic preventive maintenance: a unit is replaced at prearranged times $kT(k = 1, 2, \dots)$ independent of the failure history of the system.
- Sequential preventive maintenance: when machines and their parts become older, they need more frequent maintenance. To take this into account, time intervals become shorter as time passes by.
- Failure limit maintenance: units are replaced as soon as the failure rate or other reliability indices of a unit reach a predetermined level. All failures occurring in the meantime are corrected by replacements.

For multi-unit systems these preventive maintenance policies are:

- Group maintenance: In case a group of units is replaced at fixed time T or when the system is of age T, due to dependence (i.e. economic, stochastic or structural dependence) between the units (Nicolai and Dekker 2007), then it is called group maintenance.
- Opportunistic maintenance: when dependencies between the different units exist, the failure of one subsystem results in the opportunity to undertake replacement of the other subsystems.

Finally, in a condition-based and predictive maintenance policy the state of the system is observed. One tries to measure the condition of the equipment by monitoring different features based on for example vibration and temperature measurements. In a condition-based policy the parts are replaced when the measurement reaches a certain threshold beyond which normal functioning of the system is jeopardized. In a predictive maintenance policy replacement is performed based on a prediction of remaining useful life, which is based on the collected degradation measurements. It should be noted that the above mentioned maintenance policies are limited to the ones applicable to non-repairables, for an entire overview of all maintenance policies the interested reader is referred to H. Wang (2002).

Logistics: delays

Several delays, also called lead times, are closely related to the process of spare parts inventory and maintenance and therefore influence the downtime of the system (Dohi et al. 1998). A distinction can be made between on the one hand non-zero and zero lead times and on the other hand deterministic and stochastic lead times.

Once a failure occurs, a failure diagnosis takes place. This typically reveals which technician is found suitable to solve the problem. The response time of this internal or external (in case of outsourcing) technician will influence to some extent the downtime of the system (Haugen and Hill 1999). Moreover, not only the technician, but also the availability of the tools influences the downtime (Patankar et al. 2009). On the other hand, the failure diagnosis reveals which parts should be replaced or which spares have to be replenished (Cohen et al. 1997). Emergency replenishment, which has a much shorter lead time than a regular order, may reduce the replenishment lead time drastically. A drawback of emergency orders is that these shipments generally come at a much higher cost. Once the spare parts and the technician arrive, the on-site repair can start (repair time). Moreover, when the repair job is completed, the machine might need some startup time. Despite the fact that recent developments in technology, communication and transportation systems might reduce these delays (e.g. the diagnostic time, replenishment lead time, technician response time and startup time) drastically, they certainly are not negligible (yet) in a lot of sectors. Moreover, other delays like internal transportation time, call response time, etc. might also have an influence on the downtime of the system. These delays induced by the time necessary to find the right resources, should somehow, either by assuming negligible lead times, deterministic or stochastic lead times, be incorporated into the joint optimization models.

Logistics: multi-echelon networks

To be responsive and keep the inventory costs down, companies may utilize national and regional depots, organized in echelons. This implies deciding where to locate the spares in the multi-echelon network, how many spares to order and when to replenish these inventories. M.-C. Chen et al. (2006) are the only authors that took into account a multi-echelon spare part logistic network in a joint maintenance and inventory policy.

System characteristics: single-unit versus multi-unit systems

A single-unit system is defined as a system that consists of one component, consequently a multi-unit system thus is a system that consists of multiple components, where the components might or might not be identical. For reasons of simplicity, models assume a single-unit system repeatedly. The extension to multi-unit systems was made in several papers, as can be seen in Table 7.2, Column XIII. No papers were found that do not rely on the assumption of independent and identically distributed units. However, in most systems dependencies between the different units exist and should be taken into account to find an optimal solution. Therefore, in Section 7.2 a joint predictive maintenance and inventory policy for multi-component systems with dependence is presented.

Business objectives

When optimizing the systems, one might focus on costs, downtime, service levels, environmental impact, safety, etc. (Section 2.2.3) The minimization of the costs is most common in this type of problem (Van Horenbeek, Pintelon, and Muchiri 2010). These costs are divided into two major groups, the costs of maintenance and the costs of inventory. An overview of the costs that were taken into account in the models of the reviewed papers is given in Table 7.2. If a certain criterion is not applicable to a given joint maintenance and inventory strategy, a slash (/) is used in the table. For instance, inspection costs are only relevant in case of condition-based maintenance.

Maintenance related costs Maintenance of a system brings different types of costs. Examples are replacement costs, safety costs, inspection costs, economic losses, age dependent production costs, etc. Replacement costs might include the purchase costs of spares, the labor costs, the system downtime costs, breakage costs, etc. A distinction can be made between failure replacement costs, preventive replacement costs and condition based maintenance costs. This distinction can be explained by differences in downtime, labor costs, etc. Models based on condition-based maintenance also include a certain inspection and investment cost.

Inventory related costs The inventory costs include three major parts. Firstly, a holding cost has to be taken into account. Keeping stock is expensive because companies do not receive any interest on the blocked capital, which would be the case when the capital can be invested in other projects. Moreover, spare parts should be insured and space to stock the parts should be available. Secondly, most models include a parts ordering cost. This ordering cost is mostly a fixed amount assigned to each order that is placed. These order costs might be dependent on whether it is an emergency order or not. The parts purchasing cost is often considered a maintenance cost and sometimes an inventory cost. Thirdly, since most systems include a certain lead time and inventory can only be purchased periodically, shortage costs will be incurred when the number of spares in inventory is insufficient to service the customer.

Optimization techniques

In an attempt to find the optimal solution for a maintenance-inventory system, one could either use exact (solution) methods or heuristic ones. Given the complexity of the problem, the emphasis is on heuristic procedures. Several authors made use of simulation models (e.g. Monte Carlo simulation and discrete event simulation) to represent their problem and to find the (near) optimal values for the decision variables. As a simulation model in itself is not sufficient to find the optimal parameters, metaheuristics (e.g. genetic algorithms and scatter search) and full enumeration can be used on top of simulation to find (near) optimal solutions to the problems. Metaheuristics improve heuristics by allowing escaping from local optima (Talbi 2009). More information on widely applied metaheuristics like genetic algorithms, simulated annealing, tabu search and scatter search can be found in Glover and Kochenberger (2003). Apart from these simulation optimization methods and (meta)heuristics, recursive and iterative methods can be used to find good solutions for a given problem setting. More details on specific optimization techniques used in joint maintenance and inventory problems are provided in Section 7.1.2.

7.1.2 Existing joint maintenance and inventory optimization models

The framework on joint maintenance and inventory optimization models described in Section 7.1.1 is used to give an overview and classify the existing literature in the next paragraphs. Table 7.2 includes a summarized overview of the relevant literature in this research field and relates it to the earlier described characteristics. The characteristics that apply to all models of the reviewed papers are not included in Table 7.2. These are holding costs, corrective maintenance costs and preventive maintenance costs. Only papers including maintenance costs, inventory costs and optimization parameters related to maintenance as well as inventory (e.g. ordering time, replacement time) are included in the classification in order to only consider joint maintenance and inventory models. More details on the papers included in the overview of Table 7.2 are given in the following sections.

Falkner (1968) was the first to mention the joint optimization of inventory and maintenance in the title of his paper. By means of a dynamic programming solution procedure, he searches for the optimal initial inventory of spares and sequence of maintenance intervals for a given ordering interval T, referred to as the planning horizon. Inventory costs (a holding cost), maintenance costs (a surplus cost for corrective replacement) and a penalty cost (in case the equipment becomes inoperable before the end of the period) are all included in the model. A few years later, Osaki and his co-researchers (Osaki 1977) have introduced an order-replacement policy, in which the optimal ordering time and replacement time are jointly determined by optimizing an inventory cost function. Their model has been extended in several ways and a classification of these models was made by Dohi et al. (1998). However, Falkner's model does not optimize the ordering interval T and the order-replacement policy of Osaki (1977) does not take into account the maintenance related costs. As a consequence, these papers are not included in Table 7.2.

As the objective is to structure the field on joint maintenance and inventory optimization research for non-repairables, a thorough description and overview of all relevant literature is given in the following sections. All considered research contributions are subdivided into different sections according to the investigated maintenance (i.e. block-based, age-based and condition-based maintenance policy) and inventory policy (i.e. periodic review and continuous review inventory policy), as these two criteria determine the joint optimization problem. An exception is made for the condition-based maintenance policies, these are all discussed in one section as there is only one paper that describes a condition-based maintenance policy with a periodic review inventory policy.

Block-based maintenance policy, periodic review inventory policy

Acharya et al. (1986) developed a model that analyses a jointly optimal block-replacement and periodic spare provisioning policy for a system of n independent and identically distributed units. They assume identical block replacement and inventory ordering intervals for the single-period model and the ordering interval in the multi-period model is a multiple of the replacement interval. Moreover, the lead time was assumed to be negligible. An iterative procedure is used to optimize these coinciding intervals for a one period, as well as a multi-period model. This iterative procedure starts with choosing an interval increment and a replacement interval. The interval is incremented each iteration. For each iteration, the order-up-to-level and total cost are computed. The computation of the spares' order up-to-level is based on the inverse Laplace transform of the failure distribution. The demand for k periods and n units is approximated by a normal distribution. The corresponding expected total cost is computed with mathematical equations, including a holding cost, ordering cost, shortage cost and a corrective and preventive maintenance cost. When the stop criterion is met, the solution with the minimal total cost is selected. The authors showed that a trade-off exists between the inventory and maintenance policies by means of their multi-period model. Whereas Acharya et al. (1986) rely on a renewal function and Laplace transform to compute the mean and variance of the number of failures in a time interval, Chelbi and Aït-Kadi (2001) used a convolution

		I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI
		Inventory characteristics				Maintenance characteristics					Logistics			System		Business objectives	
		Inventory policy	Single-unit versus multi-unit inventory	Ordering cost	Shortage cost	Maintenance policy	Cost for condition based maintenance	Inspection cost	Operational cost	Economic losses	Lead time	Multi-echelon	Emergency orders	Single-unit versus multi-unit system	Independent identically distributed units	Labor constraint	Service constraint
Acharya et al.	1986	Periodic	Multi-unit	Yes	Yes	Periodic/Block	No	/	No	No	No	No	No	Multi -unit	Yes	No	No
Kabir and Al-Olayan	1994	Continuous	Multi-unit	Yes	Yes	Age-based	No	/	No	No	Random	No	Yes	Single-unit	/	No	No
Armstrong and Atkins	1996	Periodic	Single-unit	No	Yes	Age-based	No	/	No	No	Constant	No	No	Single-unit	/	No	No
Kabir and Al-Olayan	1996	Continuous	Multi-unit	Yes	Yes	Age-based	No	/	No	No	Random	No	Yes	Multi -unit	Yes	No	No
Kabir and Farash	1996	Continuous	Multi-unit	Yes	Yes	Age-based	No	/	No	No	Random	No	No	Multi -unit	Yes	No	No
Armstrong and Atkins	1998	Periodic	Single-unit	No	Yes	Age-based	No	/	Yes	No	Random	No	Yes	Single-unit	/	No	Yes
Sarker and Haque	2000	Continuous	Multi-unit	Yes	Yes	Periodic/Block	No	/	No	No	Constant	No	Yes	Multi -unit	Yes	No	No
Chelbi and Aït-Kadi	2001	Periodic	Multi-unit	Yes	Yes	Periodic/Block	No	/	No	No	Constant	No	No	Multi -unit	Yes	No	No
Yoo, Kim and Seo	2001	Periodic	Multi-unit	Yes	No	Periodic/Block	No	/	No	No	No	No	No	Multi -unit	Yes	No	No
Brezavscek and Hudoklin	2003	Periodic	Multi-unit	Yes	Yes	Periodic/Block	No	/	No	No	Constant	No	No	Multi -unit	Yes	No	No
Chen et al.	2006	Continuous inventory	Multi-unit	Yes	Yes	Age-based	No	/	No	No	Random	Yes	Yes	Multi -unit	Yes	No	No
Ilgin and Tunali	2007	Continuous Two Bin	Multi-unit	Yes	Yes	Periodic/Block	No	/	No	No	Random	No	Yes	Multi -unit	/	No	No
Elwany and Gebraeel	2008	Periodic	Single-unit	No	Yes	Condition based	Yes	No	No	No	Constant	No	No	Single-unit	/	No	No
Hu et al.	2008	Continuous	Multi-unit	Yes	Yes	Age-based	No	/	No	No	Random	No	Yes	Multi -unit	Yes	No	No
Huang et al.	2008	Periodic	Multi-unit	Yes	Yes	Periodic/Block	No	/	No	No	Random	No	No	Multi -unit	Yes	No	No
Nguyen and Bagajewicz	2008	Continuous	Single-unit	No	No	Periodic/Block	No	/	No	Yes	Constant	No	Yes	Multi -unit	Yes	Yes	No
Nguyen et al.	2008	Continuous	Single-unit	No	No	Periodic/Block	No	/	No	Yes	Constant	No	No	Multi -unit	Yes	Yes	No
Sergent et al.	2008	Continuous	Single-unit	No	No	Periodic/Block	No	/	No	Yes	Constant	No	No	Multi -unit	Yes	Yes	No
Wang et al.	2008a	Continuous	Multi-unit	Yes	Yes	Condition based	Yes	Yes	No	No	Constant	No	No	Multi -unit	Yes	No	No
Wang et al.	2008b	Continuous	Single-unit	Yes	Yes	Condition based	Yes	Yes	No	No	Constant	No	No	Single-unit	/	No	No
Xie and Wang	2008	Continuous	Multi-unit	Yes	Yes	Condition based	Yes	Yes	No	No	Random	No	No	Multi -unit	Yes	No	No
Nguyen and Bagajewicz	2009	Continuous	Multi-unit	No	No	Age-dependent	No	/	No	Yes	Constant	No	No	Multi -unit	Yes	Yes	No
Wang et al.	2009	Continuous	Multi-unit	Yes	Yes	Condition based	Yes	Yes	No	No	Constant	No	No	Multi -unit	Yes	No	No
Rausch and Liao	2010	Continuous	Multi-unit	Yes	Yes	Condition based	Yes	No	Yes	Yes	Constant	No	No	Single-unit	/	No	Yes
Wang	2011	Periodic	Multi-unit	Yes	Yes	Inspection based	No	Yes	No	Yes	No	No	Yes	Multi -unit	Yes	No	No

Figure 7.2: Characteristics of joint maintenance and inventory systems.

product computation algorithm to compute these values for different equipment life time distribution functions. Although different distribution functions were assumed, the iterative procedure that was used by these researchers was very similar. Moreover, the authors of both papers assume in their calculations that the demand for spares follows a normal distribution. Yoo et al. (2001) based their demand for spares on the total number of failure replacements during a certain time interval. Using the superposition of n statistically identical renewal processes, they were able to formulate a probability mass function. This function is evaluated using a recursive algorithm which starts with an expression for zero operating units and calculating its way up to the expression for N operating units. Once this expression is calculated, the cost function can be minimized to find the optimal values for the replacement time and spare stock level. Brezavscek and Hudoklin (2003) tested a joint block replacement and periodic review model on electric locomotives in Slovenian railways. They extend the paper of Acharya et al. (1986) by including a non-zero, deterministic lead time. As a consequence, the reorder interval is equal to the replacement interval minus the lead time. Although the paper includes an analytical mathematical model, the reader is referred to the doctoral dissertation of one of the authors for an explanation of their iterative solution procedure. Huang et al. (2008) not only generalized the model of Brezavscek and Hudoklin (2003) by including a random lead time, they also proved the existence and uniqueness of the minimum in the joint models of that type when the order-up-to level is the only decision variable in the objective function. By repeating this procedure for every replacement time in a certain interval, the minimal cost for that specific problem setting can be deduced. Their model was tested on the same example of Brezavscek and Hudoklin (2003). W. Wang (2011) used the concept of delay-time to deal with the integrated problem of maintenance and inventory. The preventive replacement policy is neither age nor block-based, but inspection-based in such a way that only the defective items identified at the time of inspection are replaced. More specifically a block-based inspection maintenance policy is considered together with a periodic fixed order interval inventory policy. The ordering quantity, order intervals and inspection intervals are jointly optimized.

Block-based maintenance policy, continuous review inventory policy

Sarker and Haque (2000) developed a joint model considering a block-based maintenance policy and a continuous review of inventory policy. The authors used a gamma distributed repair time and introduced work cells consisting of several statistically independent units to the model of Kabir and Al-Olayan (1996). A simulation model was developed and optimized through limited enumeration. Ilgin and Tunali (2007) applied a simulation optimization model, based on a genetic algorithm, in a motor block manufacturing line of an automotive factory. They investigate a block-based replacement policy and allow a variable lead time and multiple types of spares. Moreover, both single unit replacements and multi-unit replacements are performed. Cheap spare parts are ordered according to a two-bin system, whereas more expensive spares are ordered based on a continuous review policy. The main emphasis in their paper is on the development of the genetic algorithm. They could procure a cost decrease of 53% compared to the situation with the current parameter values for that specific automotive factory. Nguyen et al. (Nguyen and Bagajewicz 2008; Nguyen, Brammer, et al. 2008; Nguyen and Bagajewicz 2010) focused their research on (chemical) processing plants. Depending on the cause of the failure, different costs and repair times were assigned. They call this the failure mode. They only consider inventory for corrective maintenance and in this first paper (Nguyen, Brammer, et al. 2008), only one spare of each type could be held in stock. As a consequence of this assumption, the inventory related decisions were limited to the choice of keeping a unit in stock or not. Although they use some simplifying assumptions in their model, they were the first to add the extra dimension of labor to this kind of models. Their cost function includes as well inventory costs, maintenance costs, economic losses as labor related costs. Moreover, maintenance is not only constrained by the number of spares but also by the amount of employees. In case of binding constraints, priority rules are used to schedule maintenance. Their models were analyzed using Monte Carlo simulation. In this first paper, they consider an enumeration method to find the optimal values for both the maintenance and inventory policy and the number of employees. In a second paper (Nguyen and Bagajewicz 2008), their model was optimized by a genetic algorithm. Nguyen and Bagajewicz (2010) consider a stock of multiple units of spares. They changed their preventive maintenance policy from periodic replacement to age dependent and sequential preventive maintenance. Moreover, imperfect preventive maintenance was allowed and employee skills were added as an extra constraint to the model. Sergent et al. (2008) expand upon the work of Nguyen and his co-researchers by allowing different replacement rates for different types of spares. Monte Carlo samples are averaged in order to determine the objective value for a given set of parameters. In some cases, these values may vary greatly. Therefore, the probability of high costs, defined as risk, was analyzed and optimized too. All models of Nguyen et al. (Nguyen and Bagajewicz 2008; Nguyen, Brammer, et al. 2008; Nguyen and Bagajewicz 2010) were applied to a chemical process plant (i.e. the “Tennessee Eastman plant” problem).

Age-based maintenance policy, periodic review inventory policy

Armstrong and Atkins (1996) examined an age replacement, periodic review inventory policy, single-unit system in which the costs are minimized by searching the optimal combination of replacement (t_r) and ordering time (t_o). Their work is closely related to that of Osaki and his co-researchers, but takes into account a breakage or corrective replacement cost which makes their models joint optimization models. Based on their assumptions, they established a joint cost function which was proven to be unimodal and pseudo-convex in each of the dimensions (t_r and t_o). A pseudo-convex function behaves very similar to a convex function with respect to finding the local minimum. More information on this type of function can be found in Mangasarian (1965). In general, the global optimal combination of the replacement and ordering time is found for the Karush-Kuhn-Tucker (KKT) point (i.e. a point that satisfies the Karush-Kuhn-Tucker conditions, which is necessary for a solution in nonlinear programming to be optimal (Armstrong and Atkins 1996)) where the ordering time plus lead time is smaller than the replacement time. In their example, separate optimization comes with a cost increase of 3% compared to joint optimization. In a second paper (Armstrong and Atkins 1998), the authors considered several extensions to this model by considering an age replacement policy, where a distinction between a major and minor failure is made, and a periodic review inventory policy. A major failure, on the one hand, is resolved by replacing the machine (perfect replacement). A minor failure, on the other hand, is solved by minimal repair. Although they added an age-dependent replacement cost, a non-decreasing operating cost and a service constraint, the pseudo-convexity remains. They were able to prove the same for the addition of deterministic lead times for scheduled orders and emergency orders, but they did not succeed to prove or disprove these results when one or both (i.e. scheduled and emergency orders) of the lead times are allowed to be random.

Age-based maintenance policy, continuous review inventory policy

In contrast with Acharya et al. (1986), Kabir et al. (Kabir and Al-Olayan 1996; Kabir and Al-Olayan 1994; Kabir and Farrash 1996) make a distinction between emergency and regular ordering costs and they include a random lead time into their model, based on a Weibull distribution. Moreover, their models deal with the optimization of an age replacement and continuous review stocking policy (t, s, S), which no longer allows for a coinciding replacement and ordering time. A combination of discrete event simulation and limited enumeration has been developed to determine the optimal values for this policy. Their first model includes no more than one operating unit, which was extended to a multiple machine system in the other papers. The results of their simulation-enumeration method were compared with the results of the Barlow-Proschan policy (Barlow and Proschan 1965) and the results indicate that their method was, in general, more cost effective than the one from Barlow and Proschan. The major conclusion that can be drawn from their findings is that sequential optimization does not ensure global optimality. As no element was added to the simulation-optimization procedure to overcome falling in local optima in the work of Kabir et al. (Kabir and Al-Olayan 1996; Kabir and Al-Olayan 1994; Kabir and Farrash 1996) and Sarker and Haque (2000), several papers further developed this procedure to overcome this pitfall. Exactly the same simulation model of that of Kabir and Al-Olayan (1994) was optimized by R. Hu et al. (2008). They replaced the limited enumeration by a genetic algorithm to further optimize the (t, s, S)-policy and they managed to reduce both the costs of the objective function and the total computation time. M.-C. Chen et al. (2006) were the first to analyze a multi-echelon network. Their supply chain consists out of multiple suppliers, a distributor and different users. These users are assigned a certain priority (critical or non-critical). The researchers investigated the combination of inventory rationing, continuous review and age-based preventive replacement. The scenario based on the joint policy was compared with three other scenarios in which inventory rationing and/or preventive replacement was not included. The model was optimized using a simulation-optimization approach based on a scatter search. They used the Arena and OptQuest simulation software to perform these computations. The results show an advantage for the joint policy from the viewpoint of the entire supply chain, which is not necessarily true for the individual agents of the supply chain.

Condition-based maintenance policy, periodic and continuous review inventory policy

When measurements are used to estimate the condition of a component, the general lifetime distributions, which are based on an entire population of components, used in preventive maintenance models can be replaced by more realistic remaining lifetime distributions (Elwany and Gebraeel 2008). By dynamically updating the lifetime distributions after each inspection, more accurate information is available to set the replacement and spare ordering times. Elwany and Gebraeel (2008) integrate the updated lifetime distributions into the model of Armstrong and Atkins (1996) and rely on the same nonlinear programming solution methods to solve the problem. Inspection costs are added to this model as part of the maintenance related costs to be able to make an accurate comparison with the preventive maintenance case.

The combination of predictive maintenance and continuous review of inventory was studied by Xie and H. Wang (2008). As a consequence, an inspection cost was added to their cost formulation. Their model is very similar to the one of R. Hu et al. (2008) and a combination of simulation and a genetic algorithm was used to find good solutions for the joint strategy. Their numeric examples show the positive effects (cost decrease with an average of 3.78%) of using joint optimization instead of separate optimization. Rausch and Liao (2010) look at joint production and spares provisioning under a condition-based maintenance policy for a piece of manufacturing equipment in which the degradation level of the system is used to trigger inventory decisions. Both production lot size and due date constraint are considered. A degradation limit maintenance policy is combined with a base stock spare part inventory control policy. Constrained least squares approximation, and simulation-based optimization are applied in a heuristic two-step approach to determine the optimal decision parameters.

Wang et al. (L. Wang et al. 2008b; L. Wang et al. 2008a; L. Wang et al. 2009) wrote several papers on the optimization of condition-based replacement and spare provisioning policies. In a first model (L. Wang et al. 2008b) they consider a single-unit system, which allows them to develop a mathematical model. The computations are based on their analytical mathematical model. Part of the equations is calculated by an iteration process, whereas other equations are computed exactly. The interested reader is referred to Press et al. (1993) for more information on the iteration process. The derivation of the optimal decision parameters (the ordering time and replacement time) is based on a genetic algorithm. The extension to a number of identical units was made by L. Wang et al. (2008a). The deterioration of their system is based on Markov chains and a Monte Carlo simulation procedure, in combination with enumeration, was used to search for the optimal values of the decision variables. A third model (L. Wang et al. 2009) is optimized by simulation based on a genetic algorithm to determine the values for a joint continuous review inventory (s, S) and condition-based maintenance policy. Where the failure rate in traditional models for preventive maintenance is generally a function of the time, the failure rate in this model is a function of the deterioration level of the system. It is called a condition-based failure rate. Their model was tested on the oil monitoring data of haul truck motors introduced in the paper by Wiseman (2001) and the solution method was found to be beneficial.

7.1.3 Literature review conclusions and directions for further research

The classification of the existing literature according to the proposed framework of joint maintenance and inventory optimization models makes it possible to draw some major conclusions and suggest possible future work in this research area. The conclusions and further research are also subdivided based on the characteristics of the joint maintenance and inventory optimization models like described in the review.

Inventory characteristics

As can be concluded from Table 7.2, both periodic and continuous review policies are extensively investigated in the available literature. Both single-unit and multi-unit inventories are described as well in different publications. However, none of the reviewed joint optimization models consider quality and/or obsolescence of spare parts, although this can have a major influence on inventory costs (Kennedy et al. 2002).

Maintenance characteristics

Only two papers (Armstrong and Atkins 1998; Nguyen and Bagajewicz 2010) do not rely on the assumption of perfect maintenance or replacement, which makes the introduction of different degrees of maintenance into joint optimization models an opportunity for further investigation. Furthermore, the majority of the papers describe preventive maintenance policies (see Table 7.2, column II). However, only the most common preventive maintenance policies were examined, more specifically age-replacement and block-replacement policies. No papers seem to exist on the failure limit, repair limit and repair number counting policy. Moreover, only one paper (Elwany and Gebraeel 2008) was published on predictive maintenance strategies which use prognostic information (i.e. remaining useful life) of components for optimizing the joint maintenance and inventory policy. All published papers consider the implementation of condition-based maintenance by taking into account the current level of degradation (i.e. control limit policy), but no prediction of future degradation or prognostic information. This might be striking because of the increasing importance of predictive maintenance. Furthermore, a reduction in spare parts and inventory cost is generally considered as one of the most important indirect benefits of a predictive maintenance strategy. Due to the available prognostic information, component replacement can be anticipated and spare parts can be ordered “just-in-time”. Hence, joint optimization of a predictive maintenance and inventory policy is identified as a major direction for further research in order to quantify the impact of a predictive maintenance policy on the inventory costs.

Logistics

The downtime of the system might be influenced by several logistical delays. The production loss due to downtime of the system is certainly important to consider for bottleneck machines. Both constant and random lead times for spare parts are described in the reviewed publications. However, few papers take into account more specific time lags (e.g. response time of external technicians, failure diagnosis time). Although emergency orders are common in practice, few models take them into account. Another very interesting delay to include into the model is the mean time to corrective and preventive replacement/repair (Nosoohi and Hejazi 2011). Although the use of a constant lead time in modeling is quite common, lead times in practice are (almost) never known exactly in advance, so one might want to use a statistical distribution to model these random lead times. Only a few papers take into account this randomness in their replenishment lead time (Table 7.2, Column III). Armstrong and Atkins (1998) and Sarker and Haque (2000) add a random replacement time. As maintenance actions are delayed until a labor resource is available, an implicit random technician response time is included in the models of Nguyen et al. (Nguyen and Bagajewicz 2008; Nguyen, Brammer, et al. 2008; Nguyen and Bagajewicz 2010).

Multi-echelon networks are not uncommon in industry. However, only one paper on joint maintenance and inventory was found that took into account the different echelons in a supply chain (M.-C. Chen et al. 2006). Taking into account the interrelationship between the joint optimization problem (i.e. maintenance and inventory) and routing (e.g. mobile repairman) could be very interesting future work. Moreover, possibilities like outsourcing inventory and pooling are not considered in the available literature, although these are currently observed trends in inventory management (Kennedy et al. 2002). The effect of the recently arising concept of e-maintenance should be investigated, as the implementation of different e-maintenance concepts (e.g. remote maintenance, e-diagnostics, e-decision making) (Muller et al. 2008) will have a major impact on the joint maintenance and inventory models. By means of a collaborative environment, pertinent knowledge and intelligence become available at the right place and time, in order to facilitate reaching the best maintenance decisions. However, this knowledge should also be used to optimize the joint maintenance and inventory problem. Furthermore, new business models (e.g. product service systems (PSS)) (Meier et al. 2010) concerning maintenance and inventory management are arising fast in academics and industry. These new business models introduce a different problem environment and structure for optimizing joint maintenance and inventory systems and problems, as maintenance and inventory are controlled by an external company (i.e. the original equipment manufacturer (OEM)) rather than internally. The developed joint maintenance and inventory models should be adopted according to these current and future trends.

System characteristics

Both single-unit and multi-unit systems are extensively studied in the reviewed literature as can be concluded from Table 7.2. None of these models, however, take into account multi-unit systems with non-identical or dependent units, as units are always assumed to be independent and identically distributed. As a consequence, neither group maintenance nor opportunistic maintenance was investigated thus far. Future research should be on incorporating different levels of dependencies (i.e. structural, stochastic and economic) between units into the joint optimization models (Chapter 6), like already done in several maintenance optimization models (Nicolai and Dekker 2007; Van Horenbeek and Pintelon 2013b).

Business objectives

The objective taken into account in most of the joint optimization models is cost. In this cost function both maintenance and inventory related costs are defined. Armstrong and Atkins (1998) use an additional service constraint in their model, while Sergent et al. (2008) define an objective function to evaluate the risk of high costs. There are, however, other objectives that should or could be taken into account in certain business cases for both inventory (e.g. service levels) and maintenance (e.g. availability, reliability, maintainability and personnel management) management (Van Horenbeek, Pintelon, and Muchiri 2010). This makes multi-objective optimization for joint optimization models still an underexplored area of research. A possible opportunity where multi-objective optimization can be applied is in the models developed by Nguyen et al. (Nguyen and Bagajewicz 2008; Nguyen, Brammer, et al. 2008; Nguyen and Bagajewicz 2010) which are applied to a chemical process plant (i.e. the "Tennessee Eastman plant" problem). As safety is a very important objective in chemical process plants, these models could be extended by for example incorporating safety as an objective in a multi-objective optimization problem.

Optimization techniques

As a consequence of the complexity and the stochastic nature of the joint optimization problem, most papers base their research on simulation models or iterative solution procedures. Exact solutions are developed for relative simple models (e.g. single machine or single inventory systems). Moreover, some research on simulation in combination with alternative, more sophisticated, optimization techniques (e.g. genetic algorithms, simulated annealing) might further decrease the computational effort and provide superior results. Also some research on multi-objective optimization models (Section 7.1.3) including e.g. both availability and costs would be very interesting and valuable.

In general, most papers on joint maintenance and inventory optimization are situated on the tactical level of decision making, although maintenance and inventory also have major strategic implications for a company. Papers focusing on joint optimization of maintenance and inventory with strategic implications deal with the choice between different maintenance policies (e.g. preventive maintenance and corrective maintenance) (Sergent et al. 2008), and the combination of these maintenance strategies with different inventory policies (Armstrong and Atkins 1996). Nevertheless, papers on the strategic implications of joint maintenance and inventory models are scarce, and further research is necessary.

It can be concluded that the joint optimization of inventory and maintenance seems to be beneficial compared to separate optimization. However, several aspects are still ill-researched, which are extensively outlined. Two of the identified directions for further research are addressed in particular in Section 7.2 and Section 7.3, which together form the major contribution of this chapter.

7.2 A joint predictive maintenance and inventory policy

As identified in the conclusions of the literature review in Section 7.1.3, the development of joint predictive maintenance and inventory policy models is a major direction for further research. This is the case because accurate predictions of component failure times can be used to improve both maintenance and inventory decisions. Furthermore, component interactions are never considered in the existing joint models (Section 7.1.3). This also means that the inclusion of predictive information (RUL) in joint maintenance and inventory models for inter-dependent multi-component systems has not been considered before. Therefore, the objective here is to quantify the added value of predictive information (RUL) in joint maintenance and inventory decision making for multi-component systems considering different levels of inter-component dependence (i.e. economic and structural). A dynamic joint predictive maintenance and inventory policy is developed, which optimizes both maintenance and inventory parameters while minimizing the long-term average maintenance and inventory cost per unit time.

7.2.1 Predictive information in joint policies

Most of the joint condition-based models consider a degradation limit joint policy by taking into account the current level of degradation without considering predictive information (i.e. RUL). Although the use of predictive information can result in significant cost savings compared to a control-limit condition-based maintenance policy as shown in Chapter 6, especially for systems with component interdependence (Van Horenbeek and Pintelon 2013b). When measurements are used to estimate the condition of a component, the general life time distributions, which are based on an entire population of components, used in preventive maintenance models can be replaced by more realistic remaining lifetime distributions (Elwany and Gebraeel 2008). By dynamically updating the lifetime distributions after each inspection, more accurate information is available to set the replacement and spare ordering times. Elwany and Gebraeel (2008) integrate the updated lifetime distributions into the model of Armstrong and Atkins (1996) by considering a single-component system and single-unit storage capacity. To the best of our knowledge, this is the only paper that incorporates RUL information into the joint maintenance and inventory decision problem. This might be striking because of the increasing importance of predictive maintenance in industry (Van Horenbeek, Buré, et al. 2013). Furthermore, a reduction in spare parts and inventory cost is generally considered as one of the most important indirect benefits of a predictive maintenance strategy (e.g. see Chapter 4). Due to the available predictive information, component replacement can be anticipated and spare parts can be ordered "just-in-time". Moreover, many papers described in Section 7.1.2 acknowledge the importance of the extension of the joint predictive maintenance and inventory policies for multi-unit systems with component dependence. The objective of the presented model is to make a first contribution with regard to this gap in the available joint models.

We present a sequential optimization of both predictive maintenance and inventory for a multi-component system with component interdependencies (i.e. economic and structural dependence (Nicolai and Dekker 2007)) taking into account predictive information (RUL). The predictive maintenance model presented in Chapter 6 (Van Horenbeek and Pintelon 2013b) is extended by the inclusion of an inventory policy as presented in (Elwany and Gebraeel 2008). As we are the first to consider this type of problem, the objective is not necessarily to develop an optimal policy; rather we want to provide insight in the joint maintenance and inventory problem for a multi-component system with component interdependencies considering predictive information on component degradation. We are specifically interested in the behavior of the proposed policy with regard to changing component interdependencies. This is because due to the component interdependencies and interactions maintenance actions will be grouped and the demand pattern for spare parts changes accordingly (Van Horenbeek and Pintelon 2013b; Van Horenbeek and Pintelon 2013a). The joint policy optimizes both maintenance and inventory parameters while minimizing the long-term average maintenance and inventory cost per unit time. The added value of the joint predictive maintenance and inventory policy is compared, by means of a numerical example, to an age-based preventive maintenance policy without grouping joined with the same inventory policy as for the proposed predictive joint policy.

7.2.2 System and degradation model

Consider a series system with n non-identical components. A failure of component i causes the entire system to stop and a system and/or component failure is noticed immediately without any inspection. Maintenance is assumed to be perfect. Time is discretized with a sample time τ. Component degradation information is retrieved at each inspection date $T_{insp,z} = z\varepsilon_i, z \in \mathbb{Z}^+$ and ε_i is defined as the component inspection period such that $\varepsilon_i = s\tau, s \in \mathbb{Z}^+$. In order to perform maintenance (i.e. assumed to be replacement) on one component of the system, the entire system has to be stopped, which means system downtime is accrued. Moreover, during this downtime due to maintenance, the deterioration of the non-replaced components remains unchanged. Details on the inventory policy are given in Section 7.2.4. The degradation model is exactly the same as the one described in Section 6.2 and in Van Horenbeek and Pintelon (2013b).

7.2.3 Predictive maintenance policy

The predictive maintenance policy is the same as the one described in Chapter 6 and in Van Horenbeek and Pintelon (2013b). For the convenience of the reader, the different steps of the predictive maintenance policy, together with their corresponding sections, are repeated as follows:

- Prediction of remaining useful life by estimation of the failure probability function (Section 6.4.1)
- Individual maintenance optimization by decomposition and construction of tentative maintenance plan (Section 6.4.2)
- Calculation of penalty functions (Section 6.4.3)
- Maintenance activities grouping (Section 6.4.4)
- Maintenance execution and rolling-horizon update (Section 6.4.5)

7.2.4 Inventory policy

A system with n non-identical components and consequently non-identical spare parts is considered. For each component at most one spare component can be in stock or on order at any time. A fixed lead time L_i is considered for each component i. Denote $t_{o,i}$ as the scheduled time to order a spare for component i, where $t_{o,i} + L_i \leq t_i^{opt}$. t_i^{opt} is the optimal replacement time for component i, where t_i^{opt} equals t_i^* when component i is maintained individually and equals $t_{G_j}^*$ when component i is part of a grouped replacement of group G_j (see Section 6.3). If a component fails before t_i^{opt} it is replaced immediately if a spare is available, or else as soon as a spare arrives. If the component fails before $t_{o,i}$ an order is placed immediately. If the system is down due to a lack of spare parts, a shortage cost c_s per unit time is incurred. A cost of c_h per unit time is incurred for holding one spare part in stock for one unit time and at each order an ordering cost of c_o is incurred. We extend the model of Elwany and Gebraeel (2008) by considering a multi-component system with interdependencies. However, we adopt the same approach for the inventory policy, which is defined by replacing the traditional failure time distributions in the inventory model of Armstrong and Atkins (1996) by the predictive information (RUL). At each updating time t_i^0 the remaining useful life $F_i(t)|d_i^0$ of component i is updated. This is used to determine an optimal maintenance schedule as described in Section 7.2.3. The optimal spare ordering time $t_{o,i}^*$ can be determined at each updating time t_i^0 based on the optimal replacement time t_i^{opt} according to the sequential approach proposed by Armstrong and Atkins (1996) by defining the Joint Cost Function (JCF) as follows:

$$JCF(t_o) = \frac{c_{i,p} + S + b_i F_i^0(t_i^{opt}) + c_s \int\limits_{t_{o,i}}^{t_{o,i}+L_i} F_i^0(t)dt + c_h \int\limits_{t_{o,i}+L_i}^{t_i^{opt}} \overline{F_i^0}(t)dt + c_o}{t_{i,p}\overline{F_i^0}(t_i^{opt}) + t_{i,c}F_i^0(t_i^{opt}) + \int\limits_0^{t_i^{opt}} \overline{F_i^0}(t)dt + \int\limits_{t_{o,i}}^{t_{o,i}+L_i} F_i^0(t)dt + t_i^0} \tag{7.1}$$

where $F_i^0(t)$ equals $F_i(t)|d_i^0$. Furthermore, from the moment on a spare part is ordered the RUL of that specific component is not updated anymore.

7.2.5 Component dependencies

The same dependence parameter α_d as introduced in Section 6.5.2 is used here to model economic and structural dependence between the components. This also means that the set-up cost is defined as given in Equations 6.18 and

6.19. Stochastic dependence is not considered, however, it is straightforward to include this in the same way as stated in Section 6.5.1.

7.2.6 Numerical example

To determine the performance of the presented joint predictive maintenance and inventory policy, it is compared to an age-based policy partnered with the same inventory policy as given in Section 7.2.4. Under this policy, a unit is always maintained at its age $T_{a,i}$ or failure, whichever occurs first, where $T_{a,i}$ is a constant (Barlow and Proschan 1964). Furthermore, not only the mutual comparison of the maintenance policies is interesting; it is also valuable to determine the performance of each policy for different levels of dependence within the multi-component system. The objective of all policies is to minimize the long-term mean cost per unit time, defined as C^*.

Input data

Consider a three component system ($n = 3$) with n non-identical components. Time is discretized with a period τ equal to one and $\varepsilon_i = 5$. The component degradation parameters, as described in detail in Section 6.2.1, are given in Table 7.1. The corresponding cost and time parameters for all components are shown in Table 7.2. t_{wait} stands for the waiting time, $t_{replace}$ for the actual replacement time, t_{inst} for the installation time and the start-up time of the system and finally t_{secD} stands for the time to repair secondary damage. All these parameters determine the downtime due to preventive maintenance $t_{i,p}(t_{replace}, t_{inst})$ and corrective maintenance $t_{i,c}(t_{wait}, t_{replace}, t_{inst}, t_{secD})$. The cost of working (70), cost of transportation (120), downtime cost rate (400), shortage cost c_s (400), holding cost c_h (150) and order cost c_o (100) are also considered in the numerical example and are defined on a per unit or unit time basis. L_i equals (1,2,3).

Table 7.1: Component degradation parameters.

Component n	v_i	μ_i	α_i	β_i
1	2,00	1	100	20
2	0,40	0,2	100	3
3	0,32	0,2	100	3

Table 7.2: Cost and time parameters. Time parameters are modeled by a triangular distribution with parameters μ and σ.

$c_{i,p}$	$c_{i,c}$	t_{wait}		t_{repair}		t_{inst}		t_{secD}	
		μ	σ	μ	σ	μ	σ	μ	σ
605	5805	6	0.5	2	0,5	2	0,5	5	0.5
665	5865	6	0.5	2	0,5	2	0,5	5	0.5
475	5675	6	0.5	2	0,5	2	0,5	5	0.5

Results and discussion

The long term mean maintenance, inventory and total cost for both considered maintenance policies and different levels of dependence (α_d) are shown in Figure 7.3 and Table 7.3. When no dependence exists ($\alpha_d = 0$) the predictive policy leads to a decrease in both maintenance and inventory costs. The predictive information (RUL) allows one to better schedule maintenance based on the real degradation of the components and at the same time allows one to order spare parts "just-in-time". Moreover, due to the predictive information less maintenance activities (corrective and preventive) are performed (i.e. the component useful life is extended) (Table 7.4), which results in a lower demand for spare parts and this reduces inventory costs. When we introduce dependencies between the components ($\alpha_d > 0$), the reduction in total cost of the predictive policy compared to the age-based policy becomes bigger. This is because the predictive policy considers the component interdependencies and groups maintenance activities; while the age-based policy does not consider component interdependencies when planning maintenance (i.e. the age-based joint policy is independent on the dependence) (Section 6.7.4) (Van Horenbeek and Pintelon 2013b). However, when looking in detail to the results of Figure 7.3 and Table 7.3, we see that, as expected, the maintenance cost decreases as (α_d) increases, but on the other hand the inventory costs increase as (α_d) increases.

In other words, even with better predictability of the spare part demand, the inventory costs for the predictive policy are higher for a system with dependent components compared to the inventory costs for the age-based policy. The reason for this can be found in the changing demand pattern for spare parts due to the grouping of maintenance activities in the predictive policy when $\alpha_d > 0$. The demand for spare parts for both policies is shown in Table 7.4. As maintenance grouping becomes more cost effective when α_d increases, more maintenance actions will be performed in a grouped way in order to save set-up costs. Also for the chosen degradation and cost parameters it is cheaper to shorten the component lifetimes instead of extending them to carry out a grouped

Table 7.3: Long term mean maintenance, inventory and total cost in relation to the dependence parameter (α_d) for both the joint predictive maintenance and inventory policy and the joint age-based maintenance and inventory policy.

	Age-based joint policy			Predictive joint policy			Cost decrease (%)		
	$\alpha_d = 0$	$\alpha_d = 50$	$\alpha_d = 100$	$\alpha_d = 0$	$\alpha_d = 50$	$\alpha_d = 100$	$\alpha_d = 0$	$\alpha_d = 50$	$\alpha_d = 100$
Maintenance cost	315,58	315,58	315,58	299,48	276,62	229,07	5,10	12,35	27,41
Inventory cost	17,49	17,49	17,49	15,92	30,03	34,18	9,00	-71,66	-95,38
Total cost	333,08	333,08	333,08	315,41	306,65	263,25	5,31	7,93	20,96

Table 7.4: Number of preventive, corrective and total maintenance actions for the age-based and predictive joint policies.

	Age-based joint policy			Predictive joint policy								
				$\alpha_d = 0$			$\alpha_d = 50$			$\alpha_d = 100$		
	C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3
Preventive	94,31	147,83	121,53	84,64	149,76	123,62	98,19	155,10	133,97	99,96	157,05	135,45
Corrective	1,88	17,59	13,66	2,38	14,89	11,71	1,79	16,51	12,99	1,78	17,09	13,53
Total	96,19	165,41	135,19	87,02	165,65	135,33	99,99	171,61	146,96	101,74	174,15	148,97

Table 7.5: Long term mean detailed inventory costs in relation to the dependence parameter (α_d) for both the joint predictive maintenance and inventory policy and the joint age-based maintenance and inventory policy.

	Age-based joint policy			Predictive joint policy		
	$\alpha_d = 0$	$\alpha_d = 50$	$\alpha_d = 100$	$\alpha_d = 0$	$\alpha_d = 50$	$\alpha_d = 100$
Order cost	9,56	9,56	9,56	9,35	10,26	10,39
Shortage cost	6,52	6,52	6,52	5,39	5,63	5,50
Holding cost	1,41	1,41	1,41	1,18	14,14	18,28

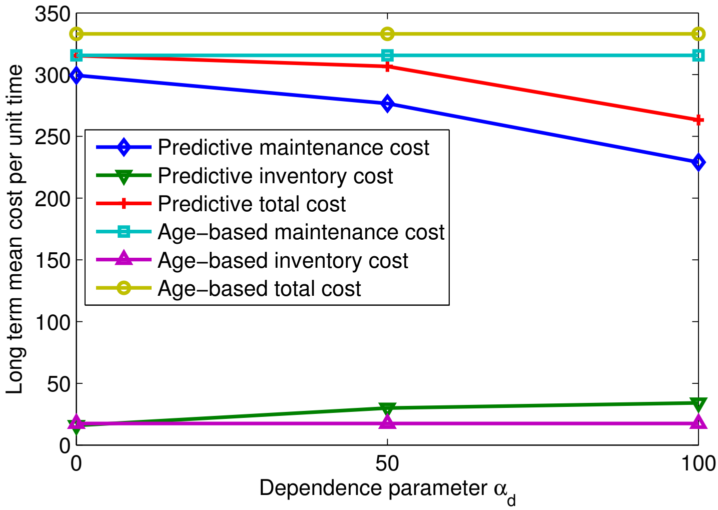


Figure 7.3: Long term mean maintenance, inventory and total cost in relation to the dependence parameter (α_d) for both the joint predictive maintenance and inventory policy and the joint age-based maintenance and inventory policy.

replacement, the demand for spare parts will rise as α_d increases. This is also shown in Table 7.4. Our proposed joint predictive maintenance and inventory policy is a sequential policy where first the timing and grouping of maintenance actions are optimized and based on this the inventory decisions are optimized. As at the first stage of determining the optimal maintenance policy the inventory considerations are ignored, all advantages of the predictive information are reflected in the decrease in maintenance cost. In fact, the maintenance decision determines the inventory policy. However, the maintenance policy does not take into account the effects of an increased demand for spare parts on the inventory costs. This increased demand results in a burden on the inventory costs, as more orders need to be placed the order costs rise and due to the shift of maintenance activities from their individual optimal times the probability of failure increases which results in higher costs due to shortage (Table 7.5). However, from Table 7.5 it becomes clear that the increase in inventory cost is mainly caused by an increase in the holding costs.

There are two major reasons for this, which can be attributed to the fact that component interactions are considered when $\alpha_d > 0$. Both are illustrated for a two component example in Figures 7.4 and 7.5. An initial situation at time t and an updated situation at time $t+1$ for both the individual and group optimal are shown. The first reason for an increased holding cost when $\alpha_d > 0$

is given in Figure 7.4 and is described in detail as follows:

1. At time t

   (a) The component individual optimal maintenance times t_1^* and t_2^* are determined.

   (b) The grouping algorithm is applied and maintenance on both components is grouped at the optimal grouped maintenance time $t^*_{G_j}$. From this optimal grouped maintenance time the optimal spare ordering time $t^*_{o,i}$ is determined through Equation 7.1. As $t = t^*_{o,2}$ an order for the second component C_2 is placed with lead time L_2.

2. At time $t+1$

   (a) The remaining useful life (RUL) of component C_1 is updated and correspondingly the individual optimal maintenance time t_1^* is updated. The remaining useful life (RUL) of component C_2 is not updated as an order for component C_2 is already placed. This means that t_2^* stays the same as at time t.

   (b) Due to the shifted individual optimal maintenance time t_1^* of component C_1, the optimal grouped maintenance time $t^*_{G_j}$ also changes (i.e. in this case to a later date). This results in an early arrival of the spare component C_2, which results in additional holding costs for component C_2 due to the shifted optimal grouped maintenance time $t^*_{G_j}$.

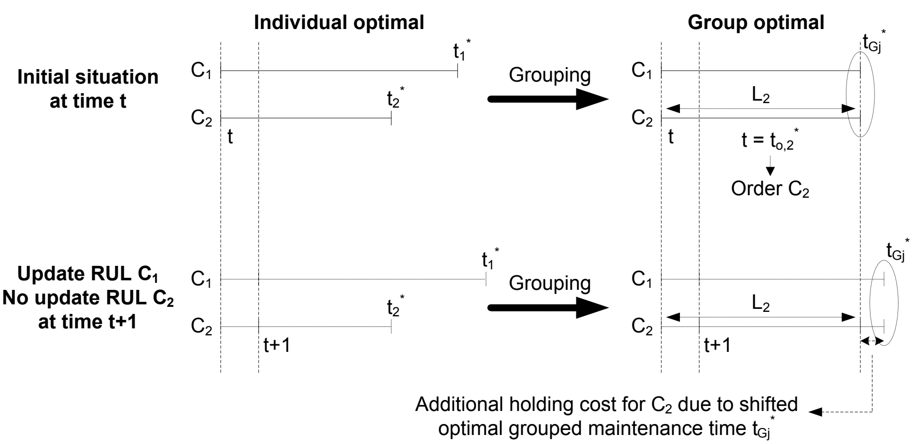


Figure 7.4: Additional holding cost due to shifted optimal grouped maintenance time $t^*_{G_j}$.

The second reason for an increased holding cost when $\alpha_d > 0$ is given in Figure 7.5 and is described in detail as follows:

1. At time t

   (a) The component individual optimal maintenance times t_1^* and t_2^* are determined.

   (b) The grouping algorithm is applied and maintenance on both components is grouped at the optimal grouped maintenance time $t_{G_j}^*$. From this optimal grouped maintenance time the optimal spare ordering time $t_{o,i}^*$ is determined through Equation 7.1. As $t = t_{o,2}^*$ an order for the second component C_2 is placed with lead time L_2.

2. At time $t+1$

   (a) The remaining useful life (RUL) of component C_1 is updated and correspondingly the individual optimal maintenance time t_1^* is updated. In this case the degradation is faster than anticipated at time t and results in a shorter component individual optimal maintenance time t_1^* at time $t+1$ (this can also be due to failure of component C_1). The remaining useful life (RUL) of component C_2 is not updated as an order for component C_2 is already placed. This means that t_2^* stays the same as at time t.

   (b) Due to the shifted individual optimal maintenance time t_1^* of component C_1, the optimal grouped maintenance time $t_{G_j}^*$ also changes (i.e. in this case to an earlier date). As component C_1 has a short lead time L_1, component C_1 can be replaced at time $t_{G_j}^*$ as planned. However, the spare component C_2 arrives late due to the long lead time L_2, which means that component C_2 is not replaced at time $t_{G_j}^*$. Moreover, component C_2 is not part of a grouped replacement anymore, which results in a later replacement at its individual optimal maintenance time t_2^*. This results in additional holding costs for component C_2 due to the late arrival of the spare part and the shift from the optimal grouped maintenance time $t_{G_j}^*$ to the individual optimal maintenance time t_2^*.

It is clear that due to component dependence ($\alpha_d > 0$) the maintenance timing of one component has an impact on the maintenance timing of another component (see for example Figures 7.4 and 7.5). Moreover, due to the adopted sequential optimization approach, the optimal maintenance timings are determined without considering the inventory parameters (e.g. spare parts in stock, spare parts on order, lead times). This leads to additional inventory costs, while all advantages of the predictive information are reflected in the maintenance cost. In order to improve the presented joint predictive maintenance and inventory policy, joint

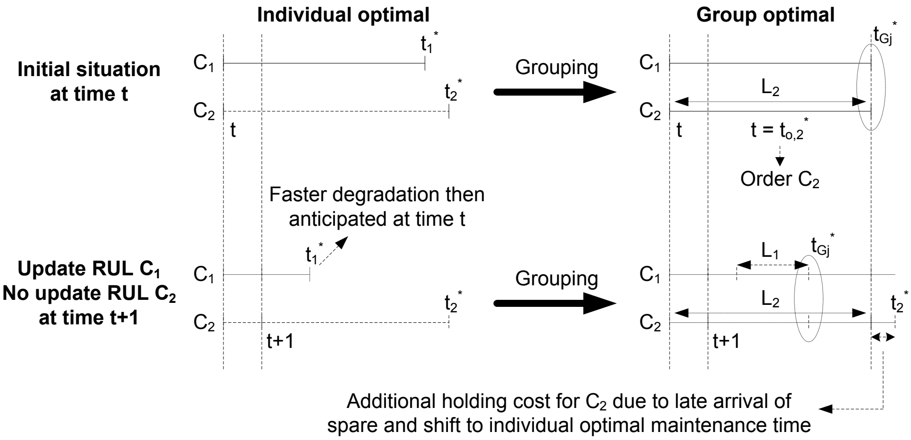


Figure 7.5: Additional holding cost due to late arrival of spare part and corresponding shift from optimal grouped maintenance time to optimal component individual maintenance time.

optimization to determine the optimal maintenance and inventory parameters should be implemented where the savings in maintenance cost by grouping should be traded-off against the additional costs in inventory.

To illustrate the potential of reducing the long-term costs even further we present an adapted joint predictive policy that specifically addresses the increase in holding cost due to late arrival of a spare part as given in Figure 7.5. The policy is adapted by performing maintenance directly when the spare part arrives rather then at the individual optimal maintenance time t_i^* (Figure 7.5). A comparison of the long-term costs for the initial predictive policy and the adapted predictive policy is given in Table 7.6. The results are as expected in the sense that the holding costs decrease and the maintenance costs increase, as maintenance is not performed at the individual optimal maintenance time t_i^*, in the adapted predictive policy. Moreover, the long-term mean total cost also decreases. This confirms that a joint optimization has the potential to reduce the total costs even further compared to a sequential optimization approach.

The results presented in this section clearly show that the use of predictive information in a joint maintenance and inventory policy has the capability to reduce the costs significantly for both multi-component systems without dependence and multi-component systems with dependence. Although, the potential to reduce the costs of a joint predictive policy even further is present by optimizing both maintenance and inventory decisions jointly rather than sequentially. This is especially true for interdependent multi-component systems.

Table 7.6: Long term mean detailed inventory, maintenance and total cost for a dependence parameter (α_d) = 100 for both the initial joint predictive maintenance and inventory policy and the adapted joint predictive maintenance and inventory policy.

	Initial predictive policy	Adapted predictive policy	Cost decrease (%)
	$\alpha_d = 100$	$\alpha_d = 100$	
Order cost	10,39	10,45	-0,55
Shortage cost	5,50	5,59	-1,60
Holding cost	18,28	14,67	19,78
Inventory cost	34,18	30,71	10,15
Maintenance cost	229,07	229,81	-0,32
Total cost	263,25	260,52	1,04

7.2.7 Joint predictive maintenance and inventory policy conclusions

A joint dynamic predictive maintenance and inventory policy for multi-component systems considering different levels of dependence (i.e. economic and structural) is presented. The joint policy optimizes both maintenance and inventory parameters while minimizing the long-term average maintenance and inventory cost per unit time. We are the first to consider a joint policy that considers predictive information for a multi-component system with dependence. The results show that the developed joint predictive maintenance and inventory policy reduces the long-term total (i.e. maintenance and inventory) costs for both multi-component systems without dependence and multi-component systems with dependence. For systems without dependence both the maintenance cost and inventory cost decrease due to the better predictability of spare part demand based on the predictive information. For systems with dependence the conclusions are slightly different. The total cost decreases when the dependence increases (i.e. due to grouping of maintenance activities). But due to the adopted sequential optimization approach the optimal maintenance schedule determines the inventory decisions, which leads to an increasing inventory cost when the dependence between the components increases. This means that all advantages of the predictive information for dependent multi-component systems are reflected in the maintenance costs, rather than in the inventory costs.

The results indicate that a real joint optimization, opposed to the sequential proposed here; of the maintenance and inventory decisions has the potential to reduce the costs even further, especially for dependent multi-component systems.

Furthermore, as opposed to the perception in most of the publications, where the use of predictive information is perceived to reduce inventory costs due to the better predictability of spare part demand, the availability of this predictive information does not guarantee a decrease in inventory costs in multi-component systems with dependence. It is shown that both maintenance and inventory policy have to be adjusted to each other to fully exploit the benefits of predictive information in a joint policy for dependent multi-component systems.

As this is only the first contribution to the literature considering a joint predictive maintenance and inventory policy for multi-component dependent systems, many directions for future research can be derived. Joint optimization of predictive maintenance and inventory, opposed to sequential optimization, should certainly be investigated more in detail in order to determine its improvement potential.

7.3 The effect of maintenance quality on spare parts inventory for a fleet of assets

As indicated in Section 7.1.3 of the literature review, spare parts and maintenance quality for a multi-system environment are not considered in any of the published papers. Therefore, this section considers the effect of fleet size on a joint policy of maintenance and spare parts inventory when spare parts and/or maintenance are of varying quality. We consider N identical one-component systems subject to age-based replacement, and with a single echelon periodic review spare-parts policy. The joint policy is optimized with regard to the long-run total cost per unit time, where the cost components include both replacement and inventory related costs. In particular, we are interested in the effect of spare parts quality and the size of the fleet on the variability in the demand for spare parts. Furthermore, the effects of changing lead time, different failure characteristics, and simultaneous deployment of the N systems over a finite horizon on the optimal joint policy are investigated. We develop a stochastic simulation model to investigate these effects. We find that the scale effect varies with the quality of spare parts: the poorer the quality of spare parts, the smaller the scale effect. Our approach allows the value (e.g. cost of poor quality spare parts) in spare parts provisioning for maintenance to be quantified.

7.3.1 Problem delineation

We are broadly concerned with the effect of the quality of maintenance simultaneously upon a joint maintenance and inventory policy. The model we develop allows one to explore value in spare parts provisioning. We suppose that maintenance quality is represented by component or installation quality or both, and that components are heterogeneous, with component lifetimes arising from a mixture of populations of weak and strong components, in the manner proposed by Scarf and Cavalcante (2012). Component lifetimes may reflect component quality directly, or may reflect the quality of installation. By modeling component lifetime following replacement as a simple two-population mixture, their idea is that a proportion of components will fail very early following replacement. In Scarf and Cavalcante (2011), the effect of such component quality upon maintenance and inventory policy was investigated for a simple one-component system. We now extend this analysis to a fleet of N identical one-component systems, and investigate in particular how the effect of maintenance quality on maintenance and inventory is modified by the scale of the fleet. One would expect that, for a fleet of identical assets subject to maintenance, the demand process for spare parts will depend on the nature of the maintenance, the size of the fleet, and to some extent the nature of the deployment of the assets. A preliminary analysis of this problem was carried out in Van Horenbeek, Scarf, et al. (2012). We extend that paper here by considering all discussed aspects (i.e. spare part quality, fleet size, nature of maintenance, and nature of deployment of the assets) on the optimal joint policy. For a large fleet, with each unit subject to age-based replacement (Barlow and Proschan 1965), we might expect the spare parts demand process to be Poisson, and poor quality of maintenance will simply increase the demand rate and consequently increase costs in a rather straightforward way. For a small fleet, the demand process may become lumpy and intermittent, in the sense of Syntetos et al. (2005), and poor quality of maintenance may increase costs in a more complex way. Such increasing costs may arise due to increasing frequency of stock-outs. With block replacement, scale effects (that is, the effects that depend on the size of the fleet) may be exaggerated as component replacements are synchronized. If assets are simultaneously deployed from new and are subject to age-based replacement, then we might expect the demand process to be initially lumpy, and then later in the deployment to become more Poisson-like. Then, ideally, the spare parts inventory policy should be adapted to the time since deployment; in other words, the spare parts inventory should expect to incur infrequent but very large demands early in deployment, with demand becoming more Poisson-like later. Of course, this is all intuitively known by inventory managers. The aim is to quantify these effects so that the economic efficiency of a joint inventory and maintenance policy might be improved systematically. This section makes a start at addressing some of these issues.

None of the available literature on joint maintenance and inventory models considers the effect of maintenance quality on the joint policy (Sections 7.1.3 and

7.1.3). In this way, our research is innovative because to our knowledge we are the first to consider the role of maintenance quality in spare part provisioning for maintenance, and therefore it makes a useful contribution to this extensive literature. The model we present allows one to explore the value in spare parts provisioning for maintenance. In this section in particular, we consider a fleet of identical assets, each a one component non-repairable system, subject to age-based replacement. We suppose the inventory policy is a single echelon periodic replenishment policy. This assumption makes our research most related to the work of Armstrong and Atkins (1996) and Armstrong and Atkins (1998), as they also consider an age replacement policy, and a periodic review inventory policy. However, they looked at models for single-unit systems, and a single-unit inventory. So we not only extend their work by introducing maintenance quality into the problem formulation, but also by considering a fleet of assets, and a multi-unit inventory. Furthermore, we investigate the effect of the nature of the deployment of the assets on the joint optimal policy, which has not been considered before. We suppose that the fleet may or may not be simultaneously deployed. We jointly optimize the age-based replacement policy and the periodic inventory policy. Due to the nature of the problem, most papers dealing with an advanced (e.g. multi-unit inventory) combined policy make use of simulation to solve the problem (Van Horenbeek, Buré, et al. 2013). Moreover, it is stated that research on simulation in combination with more sophisticated optimization techniques (e.g. genetic algorithms (GA)) might further decrease the computational effort, and provide superior results (Section 7.1.3). Also, the predominant approach is the optimization of one criterion, namely cost, in the majority of the cases (Van Horenbeek, Buré, et al. 2013). Here, we take this approach, thus presenting a combined approach of simulation with a genetic algorithm to determine the corresponding cost-optimal policy.

7.3.2 The system, and corresponding cost formulations

Consider N identical assets, each of which is a non-repairable, single component, single failure mode system; that is, each asset comprises a socket and a component which together perform an operational function (Ascher and Feingold 1984). On substitution of the existing component with a new component, the system is renewed. Failure of the component implies system failure; and system failures have consequences for the cost and availability of the operational function.

Maintenance policy

Each asset is subject to an identical age-based replacement policy (Barlow and Proschan 1965): replace the component on failure, or at age T, whichever occurs first. In this model, no consideration is given to the spare parts provisioning policy, implicitly assuming that a spare part is available immediately upon request. We do not make this assumption. Instead, we suppose that when a spare component is available, replacement is immediate; and when a spare part is not available, replacement is delayed until a spare part becomes available. Note here that preventive replacement therefore may not always occur at age T; there may be a delay if there is no spare part readily available. Note also that, as long as the system is operational, no cost consequences are related to this preventive replacement delay. The related maintenance cost for a replacement is either C_p for a preventive replacement or C_c for a corrective replacement. In contrast to a preventive replacement, a corrective replacement introduces downtime τ_r of the system. The corresponding downtime cost is $\tau_r C_d$. To reduce downtime costs, if corrective and preventive maintenance is simultaneously required for different assets, corrective action is prioritized over preventive action. When not enough spare parts are available to perform preventive maintenance action(s), after the corrective action(s) have been taken, preventive maintenance action(s) are shifted until new spare parts become available, which is at the next replenishment of inventory.

Inventory policy

Consider a single echelon periodic replenishment policy for the N assets (i.e. a multi-unit inventory), that is, a single, common warehouse that supplies spare parts to all assets. Every R time units, order stock to replenish the inventory from the current inventory position S_t up to a fixed level of S stock units (i.e. an (R, S) policy). The current inventory position S_t takes into account outstanding orders and backorders, while the stock on hand S_o defines the immediately available spare parts for maintenance purposes. The inventory related costs are subdivided into three categories: order cost, shortage cost, and holding cost. The order cost C_o occurs when at inventory review $S_t < S$, and the order size equals $O = S - S_t$. Shortage or downtime cost C_d is incurred over the time a failure replacement is delayed because of spare parts shortage (e.g. due to late arrival of spare parts). Holding cost C_h is the cost for holding one spare part in inventory for one unit of time. The total holding cost depends on the number of spare parts in stock, and the time in inventory (i.e. from its arrival to the start of its operation at a replacement). The holding cost is only charged when spare parts are available for immediate replacement. This approach means the holding cost is calculated based on the stock on hand.

Component quality

Suppose that the stockpile of components is heterogeneous, some weak, some strong; such heterogeneity may be the result of poor installation, or poor component quality (leading to a short component lifetime). Let the proportion of weak components be p. The time to failure distribution is assumed to be a mixture modeled as $F(t) = pF_1(t) + (1-p)F_2(t)$, and we use Weibull distributions for the sub-populations:

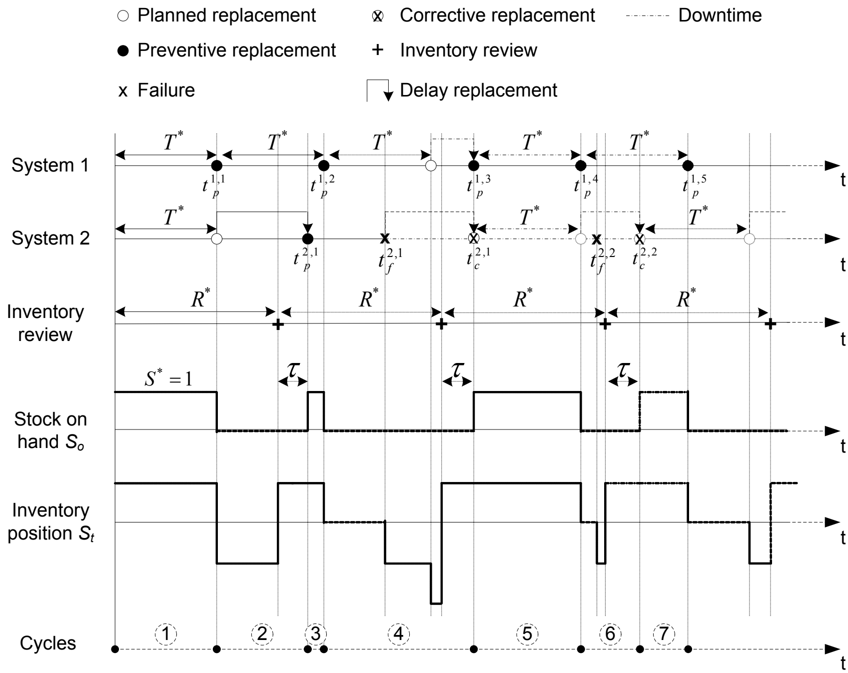
$$F_i(t) = 1 - exp(-(t/\eta_i)^{\beta_i}) \tag{7.2}$$

For a discussion of the properties of such mixtures, see (R. Jiang and Murthy 1998).

Joint maintenance and inventory policy

Based on the defined maintenance policy, inventory policy, and component quality, it is possible to illustrate the behavior of the considered system and policy. Figure 7.6 shows the joint maintenance and inventory policy for a hypothetical case considering two systems. Furthermore, the procedure to calculate the total cost by aggregating all maintenance and inventory related costs over the specified time horizon h is displayed in the table at the bottom of Figure 7.6. The aggregation of costs is done by considering different maintenance cycles over the time horizon h, where a cycle is defined by the time between two successive replacement actions (i.e. either preventive or corrective) on one of the considered systems. To illustrate the adopted modeling approach, a detailed description for each cycle defined in Figure 7.6 is given as follows.

Cycle 1. At the start, the stock on hand S_o equals S^*, where $S^* = 1$ is assumed. This assumption also means that the current inventory position $S_t = 1$. It is assumed that both systems are as good as new, which means that the preventive replacement of both is planned at age T^*. However, there is only one spare part immediately available (S_o). Therefore, system 1 is replaced at time $t_p^{1,1}$, and system 2 has to wait until the replenishment of inventory before the planned replacement can be executed. Note that system 2 stays operational until the replenishment of inventory, or until it breaks down. As the demand for spare parts is two, the current inventory position drops to $S_t = -1$ (i.e. one backorder), and the stock on hand becomes $(S_o) = 0$. The corresponding cost for this cycle can be seen in the table at the bottom of Figure 7.6. This cost calculation applies to each cycle.



	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5	Cycle 6	Cycle 7
Shortage time	-	-	-	$\left(t_c^{2,1} - t_f^{2,1}\right)$	-	$\left(t_c^{2,2} - t_f^{2,2}\right)$	-
Holding time	$\left(t_p^{1,1} - 0\right)$	-	$\left(t_p^{1,2} - t_p^{2,1}\right)$	-	$\left(t_p^{1,4} - t_p^{1,3}\right)$	-	$\left(t_p^{1,5} - t_c^{2,2}\right)$
Ordering cost	-	C_o	-	C_o	-	C_o	-
Replacement cost	C_p	C_p	C_p	$C_p + C_c$	C_p	C_c	C_p
Downtime cost	-	-	-	$C_d \cdot \left(t_c^{2,1} - t_f^{2,1} + \tau_r\right)$	-	$C_d \cdot \left(t_c^{2,2} - t_f^{2,2} + \tau_r\right)$	-
Holding cost	$C_h \cdot \left(t_p^{1,1} - 0\right)$	-	$C_h \cdot \left(t_p^{1,2} - t_p^{2,1}\right)$	-	$C_h \cdot \left(t_p^{1,4} - t_p^{1,3}\right)$	-	$C_h \cdot \left(t_p^{1,5} - t_c^{2,2}\right)$
Cycle cost	$C_p +$ $C_h \cdot \left(t_p^{1,1} - 0\right)$	$C_o + C_p$	$C_p +$ $C_h \cdot \left(t_p^{1,2} - t_p^{2,1}\right)$	$C_o + C_p + C_c +$ $C_d \cdot \left(t_c^{2,1} - t_f^{2,1} + \tau_r\right)$	$C_p +$ $C_h \cdot \left(t_p^{1,4} - t_p^{1,3}\right)$	$C_o + C_c +$ $C_d \cdot \left(t_c^{2,2} - t_f^{2,2} + \tau_r\right)$	$C_p +$ $C_h \cdot \left(t_p^{1,5} - t_c^{2,2}\right)$

Figure 7.6: Overview of joint maintenance and inventory policy, and corresponding cost calculations.

Cycle 2. The inventory position is reviewed at R^*, and $S^* - S_t = 2$ spare parts are ordered. Actual replenishment of the inventory happens after a lead time τ. System 2 is still operational when the inventory is replenished. Therefore, a postponed preventive replacement is performed on system 2 at time $t_p^{2,1}$, and $S_t = S_o = 1$.

Cycle 3. The preventive maintenance of system 1 is executed at time $t_p^{1,2}$ as the age of system 1 reaches T^*, and a spare part is immediately available $S_o = 1$. Both inventory statistics become $S_t = S_o = 0$ after the preventive replacement.

Cycle 4. System 2 fails at time $t_f^{2,1}$; and as $S_o = 0$, system downtime (i.e. shortage cost) is accrued, and the corrective replacement is postponed until a spare part becomes available. Preventive replacement of system 1 is planned because its age equals T^*. However, no spare part is available for preventive replacement ($S_o = 0$), so the preventive replacement of system 1 is postponed until a spare part becomes available. Note that system 1 stays operational until the replenishment of the inventory, or until it breaks down. Both a corrective and preventive backorder are outstanding, and therefore $S_t = -2$. Next, the inventory is reviewed at time R^* since the last review, and $S^* - S_t = 3$ spare parts are ordered. Actual replenishment of the inventory happens after a lead time τ, and both the postponed corrective (system 2), and preventive replacement (system 1) are conducted at respectively $t_c^{2,1}$, and $t_p^{1,3}$. The inventory statistics become $S_t = S_o = 1$ after the postponed replacements.

Cycle 5. The preventive replacement of both systems is planned as their age reaches T^*. However, there is only one spare part immediately available $S_o = 1$. Therefore, system 1 is replaced at time $t_p^{1,4}$, and system 2 has to wait until the replenishment of inventory before the planned replacement can be executed. Note that system 2 stays operational until the replenishment of inventory, or until it breaks down. As the demand for spare parts is two, the current inventory position drops to $S_t = -1$ (i.e. one backorder), and the stock on hand becomes $S_o = 0$.

Cycle 6. System 2 fails at time $t_f^{2,2}$ during the waiting time for a spare part. Because $S_o = 0$, system downtime is accrued, and the corrective replacement is postponed until a spare part becomes available. Next, the inventory is reviewed at time R^* since the last review, and $S^* - S_t = 2$ spare parts are ordered. Actual replenishment of the inventory happens after a lead time τ, and the postponed corrective replacement (system 2) is conducted at time $t_c^{2,2}$. This makes system 2 operational again after a corrective replacement time τ_r. The inventory statistics become $S_t = S_o = 1$ after the postponed replacement.

Cycle 7. The preventive maintenance of system 1 is executed at time $t_p^{1,5}$ as the age of system 1 reaches T^*, and a spare part is immediately available $S_o = 1$. Both inventory statistics become $S_t = S_o = 0$ after the preventive replacement.

Note that some additional holding or shortage cost may have to be added to the total cost at the end of the time horizon h if spares are left in inventory since the last replacement, or if any failed system awaits replacement due to spare part shortage.

7.3.3 Simulation and optimization methodology

Using the exact demand process, the objective is to determine the joint optimal policy $\theta^*(p,N) = \theta^* = (T^*, R^*, S^*) = \{T^*(p,N), R^*(p,N), S^*(p,N)\}$, and the long-run total cost per unit time or cost-rate of this policy. Denote this optimal cost by $C^*(\theta^*; p, N)$. The long-run total cost per unit time per asset, $C^*(\theta^*; p, N)/N$, is called the cost-rate C^*_M. We will then investigate the effect of p and N on the cost-rate. As a consequence of the complexity and stochastic nature of the joint optimization problem, most papers base their research on simulation models or iterative solution procedures (Section 7.1.3) (Van Horenbeek, Buré, et al. 2013). Exact solutions are only developed for relative simple models (e.g. single machine or single inventory systems) (Armstrong and Atkins 1996; Armstrong and Atkins 1998). As acknowledged by many studies, it is very difficult or even impossible to derive an analytic formulation for more complex joint optimization problems (Van Horenbeek, Buré, et al. 2013). The problem tackled in this section is complex due to the fact that we consider a fleet of assets in combination with a multi-unit inventory (Van Horenbeek, Buré, et al. 2013). This problem introduces complex interactions between the assets in relation to stock related events (i.e. ordering, holding, and shortage), as the inventory is common for all assets. Moreover, the exact demand process should be used to quantify the effects of p and N on the joint optimal policy. Therefore, we implement a stochastic simulation procedure to evaluate the performance of different joint maintenance and inventory policies.

Monte Carlo simulation approach

A discrete-event stochastic simulation model is constructed to evaluate the performance of the joint maintenance and inventory policy for a specified set of decision variables $\theta = (T, R, S)$. The logic of the adopted simulation algorithm is depicted in Figure 7.7, and described next.

Step 1. First, the input parameters $(\tau, \tau_r, C_d, C_p, C_c, C_o, C_h, h, \eta_1, \eta_2, \beta_1, \beta_2, p, N)$ are set according to the investigated context. An initial value is given to the joint optimization parameters $\theta = (T, R, S)$ for the joint policy.

Step 2. Based on T, the preventive replacement time $t_p^{i,j}$ for each asset i is determined. This calculation results in a vector $T_p = (t_p^{1,j}, \ldots, t_p^{N,j})$

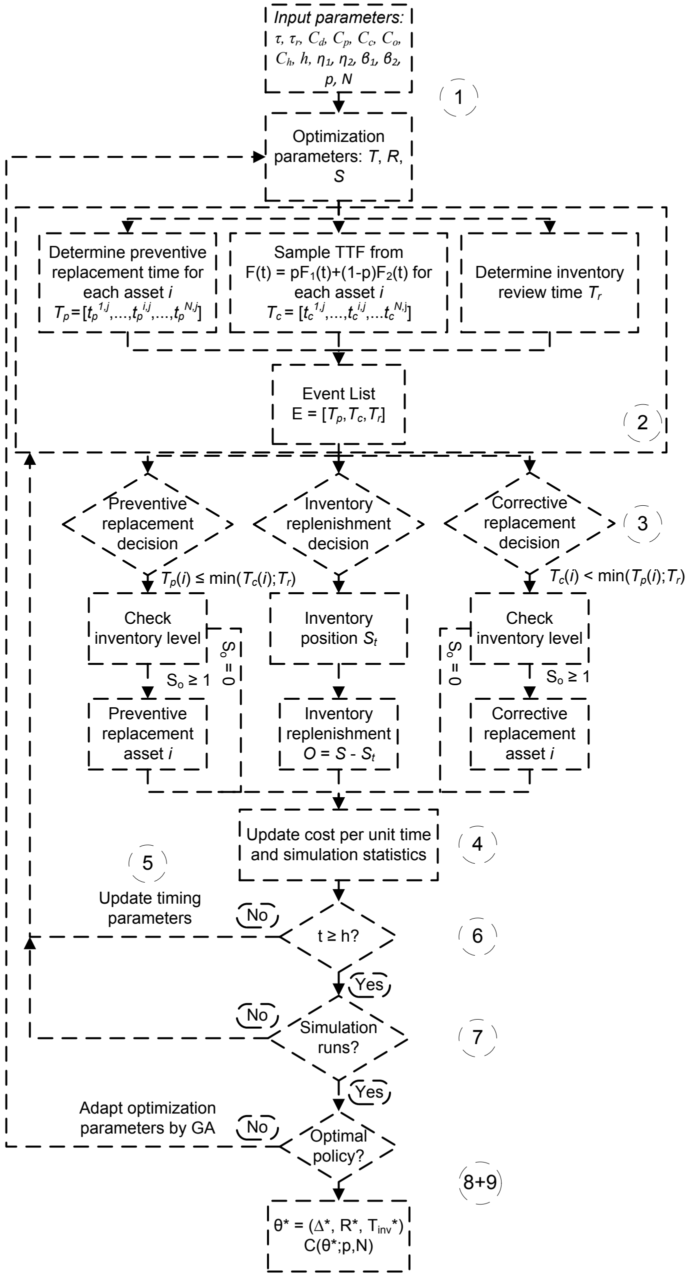


Figure 7.7: Flow chart of the simulation model.

that describes the preventive replacement times for all assets i. Failures of components are simulated by Monte Carlo sampling from the mixed time to failure distribution as described in Equation 7.2. This sampling of the failure distributions ensures that the exact demand process is considered in the simulation model. The vector $T_c = (t_c^{1,j}, \ldots, t_c^{N,j})$ contains the corrective replacement times for all assets i, where initially $t_c^{i,j} = t_f^{i,j}$. Review of the number of spare parts in inventory is performed at $T_r = nR$ with $n = \lceil t/R \rceil$. Based on the preventive replacement times T_p, corrective replacement times T_c, and inventory review time T_r for all N assets, an event list $E_t = (T_p, T_c, T_r)$ at simulation time t is constructed.

Step 3. As a discrete-event simulation model is considered, the next event $(\min(T_p, T_c, T_r))$ is determined from E_t. The type (preventive replacement, corrective replacement, or inventory review) of the next event, together with the asset i on which this action should be taken, is determined (see Figure 7.6). It is of course possible to have several events at the same time on different assets. Corrective replacement actions or events get the highest priority, as these have a direct effect on the long-run total cost per unit time because of the incurred downtime. From an operational point of view, it is also more logical to first replace components in failed equipment to get the asset again to a working state, as this has a direct impact on the productivity of the plant. A corrective action on asset i is necessary when $T_c(i) < \min(T_p(i), T_r)$. On the other hand, a preventive maintenance replacement is necessary when $T_p(i) \leq \min(T_c(i), T_r)$. Replacement of a component can only happen when the inventory level $S_o \geq 1$ at the time of replacement. If this is not the case, the replacement of the component is postponed until the next replenishment of the inventory. For a preventive replacement, this means we have a higher probability of failure of the component until the inventory is replenished as the component stays in an operating state beyond the initially planned preventive replacement time. A postponed corrective replacement means a higher downtime, and results in higher long-run total cost per unit time for the considered asset i. The inventory is replenished at time T_r, and the number of spare parts ordered $O = S - S_t$.

Step 4. When the events on all N assets at the current simulation time t are performed as described in step 3, the total cost per unit time is updated according to the procedure shown in Figure 7.6.

Step 5. The timing parameters $t_p^{i,j}$ and $t_c^{i,j}$ for each asset i for which a replacement happened at time t, and T_r, when the inventory was reviewed at time t, are updated. The simulation time t is updated.

Step 6. When the current simulation time t exceeds the simulation time horizon h, the simulation for this repetition for the given parameters ends.

Step 7. Repeat steps 2-6 for a specified number of simulation runs.

Step 8. From the aggregate results of all simulation runs, the average long-run total cost per unit time or cost rate for the given joint policy is determined.

Step 9. To find the optimal policy, the optimization parameters (T, R, S) are adapted. A genetic algorithm (GA) (Holland 1962) is used to determine the optimal policy $\theta^* = (T^*, R^*, S^*)$, and its corresponding optimal long-run total cost per unit time $C^*(\theta^*; p, N)$. Details on this genetic algorithm approach are given in the following section.

Genetic algorithm optimization approach

As a simulation model like that presented in Section 7.3.3 is not sufficient to find the optimal parameters, metaheuristics (e.g. genetic algorithms and scatter search) and full enumeration can be used on top of simulation to find (near) optimal solutions to the defined problem (Van Horenbeek, Buré, et al. 2013). Because of the complexity of the optimization problem, the objective function (i.e. cost per unit time) is a complicated multivariate, non-linear function that cannot be put explicitly in an analytical form. Consequently, the economic evaluation of a joint policy is not feasible through analytical methods (Cantoni et al. 2000). Furthermore, many combinations of the decision variables exist, so the search space for the optimization becomes tremendously large (i.e. excluding total enumeration as an option). As stated in Ilgin and Tunali (2007), using simulation in the optimization process includes several specific challenges. The major issues to address when using simulation modeling in optimization can be summarized (Ilgin and Tunali 2007): no analytical expression of the objective function exists, the objective function is a stochastic function of the deterministic decision variables, performance measures could have many local extremes, the parameter space is not continuous, and the search space is not compact. However, as described in Ilgin and Tunali (2007), these issues are a direct recommendation for the use of genetic algorithms (GAs) because these are able to handle these issues in a reliable way. Therefore, we propose an approach where the simulation model is embedded within a genetic algorithm to find the optimal policy $\theta^* = (T^*, R^*, S^*)$, and its corresponding optimal long-run total cost per unit time $C^*(\theta^*; p, N)$. Genetic algorithms have already been used to optimize several joint maintenance and inventory policies (Van Horenbeek, Buré, et al. 2013). A short description of the GA and its corresponding parameters is given here; for further details, the interested reader is referred to Goldberg (1989). A GA is a heuristic that mimics the process of natural evolution and survival of the fittest based on crossover and mutation on the initial population (i.e. a set of values of the decision variables (T, R, S) as potential solutions to the decision problem). The values of the different decision variables (T, R, S) (i.e. individuals) are represented by a chromosome defined as an array of binary numbers. Then, these individuals are evaluated in terms of their fitness (i.e. their corresponding objective function value). The evaluation of the fitness of an individual is performed by running through steps 1-8 of the simulation model presented in Section 7.3.3. In this way, the simulation model is embedded in the GA. A different number of iterations (by repetition of steps 1-9 of the model presented in Section 7.3.3), referred to as generations of the GA, are performed to improve the objective or fitness function(s), which in this case is the long-run total cost per unit time or cost rate C_M^*. Each generation of the GA generates a new population, where the individuals with a better fitness function (i.e. lower cost rate C_M^*) have a higher probability to be selected as parents, in resemblance to the natural principle of 'survival of the fittest'.

As mentioned earlier, many combinations of the decision variables exist. Therefore, total enumeration, where a full Monte Carlo simulation with accurate statistics for each alternative should be performed, is infeasible. If instead the search is guided by a GA, it is still impractical and time consuming to run a full Monte Carlo simulation for each individual in the populations. Considering that in the GA approach the best chromosomes appear a large number of times in the successive generations whereas the bad ones are readily eliminated, a solution to this problem is provided by the drop-by-drop approach introduced in (Cantoni et al. 2000; Marseguerra, Zio, and Podofillini 2002). In this approach, for each proposed individual, a Monte Carlo simulation with a limited number of iterations is run (e.g. 200). During the evolution of the GA, an archive of the best individuals and their corresponding objective functions is kept. Each time an individual is re-proposed, the newly computed estimates on the objective function are accumulated with those stored in the archive. As good individuals are proposed a large number of times, statistically significant results are obtained at the end (Cantoni et al. 2000).

The design parameters of the GA that we adopt can be summarized as follows. The number of individuals in each population for the GA is set to 50, and the maximal number of generations is 100. Scattered crossover is selected as the crossover function with a crossover fraction of 0.8. This crossover fraction specifies the fraction of individuals in the next generation that are created by crossover. Mutation produces the remaining individuals in the next generation by using a uniform mutation function with a mutation probability of 0.005. A tournament selection function is used as the parent selection method. To validate the performance (i.e. optimality requirement and CPU time) of the GA, a comparison with simulation optimization by numerical enumeration is performed for the parameter values shown in Table 7.7. For the numerical enumeration, a part of the entire search space is considered by defining a range of values for each decision variable (i.e. $T = 0$ through 60, $R = 1$ through 25, and $S = 1$ through 5). The results of the comparison are shown in Table 7.8.

These results clearly justify the combination of simulation and GA to find the optimal decision variables for the joint maintenance and inventory policy. The maximal cost increase of finding a (near) optimal solution by the GA is only 1.68% while the CPU time is reduced with at least 92.16%. Moreover, in most cases, the GA approach finds the global optimal policy $\theta^* = (T^*, R^*, S^*)$. Mark that the simulation time horizon for the results in Table 7.8 is a finite 100 time units. To derive long-term statistics, it would however be necessary to perform simulations over a much longer time horizon h. As for the finite time horizon ($h = 100$), and N is five, already more than 31 hours of CPU time is necessary to perform a limited numerical enumeration. This clearly illustrates that full enumeration by simulation as an optimization approach is not always feasible for the considered problem.

7.3.4 Numerical example and discussion

A first simulation optimization based on the parameters given in Table 7.9 is performed. This simulation is referred to as the base simulation in the remainder of this chapter. In addition to the system description in Section 7.3.2, we assume that all assets are put into operation from $t = 0$ onward, and have age $T_{i,initial}$ (i.e. non-simultaneous deployment). In the base case, one simply runs the simulation for a warm-up period, and then collects statistics for the further simulation time, leaving the warm-up period out. To gain some insight into the effects of simultaneous deployment of all assets, finite mission time, lead time, and failure characteristics on the joint maintenance and inventory policy, a number of case problems are constructed. For each case problem, the optimal policy $\theta^* = (T^*, R^*, S^*)$ and its corresponding optimal long-run total cost per unit time $C^*(\theta^*; p, N)$ are derived. The results of the base simulation and the case problems are given and discussed in the following sections.

Results base simulation

The parameter values for the base case are given in Table 7.9. These parameters have arbitrary units defined by the authors. However, their relative sizes are typical of those that might be encountered in a practical context so that for example the ratio defined by the cost of failure replacement to the cost of preventive replacement is six. We consider particular parameters (e.g. N and p) more generally because we are especially interested in the behavior of the optimal policy when these parameters change. The results for the base simulation, defined by the parameters given in Table 7.9, are shown in Table 7.10. An overview of the optimal policy ($\theta^* = (T^*, R^*, S^*)$), detailed costs

Table 7.7: Parameter values for GA validation.

t_u	τ	τ_r	C_d	C_p	C_c	h	C_o	C_h	η_1	η_2	β_1	β_1	p	N
1	1	0,5	6000	1000	5000	100	200	50	10	70	3	3	0-0,1-0,3	1-2-5

Table 7.8: Comparison between total enumeration and the GA approach.

		Numerical enumeration					Genetic algorithm					Performance metrics		
N	p	T^*	R^*	S^*	C^*	CPU time (s)	T^*	R^*	S^*	C^*	CPU time (s)	Optimal point?	Cost increase (%)	CPU time reduction (%)
1	0	28	20	1	89,58	40908	29	21	1	90,84	1589	No	1,41	96,11
1	0,1	37	6	1	124,71	51995	38	6	1	126,81	3226	No	1,68	93,80
1	0,3	51	1	1	183,10	53148	52	3	1	184,88	4099	No	0,97	92,29
2	0	28	7	1	147,56	82557	28	7	1	148,47	4200	Yes	0,62	94,91
2	0,1	36	1	1	200,60	84364	35	1	1	202,75	4655	No	1,07	94,48
2	0,3	51	1	1	318,92	86767	51	1	1	318,90	6798	Yes	0,00	92,16
5	0	26	1	1	290,96	112896	26	1	1	289,12	7827	Yes	-0,63	93,07
5	0,1	34	1	1	425,25	115380	34	1	1	425,60	8166	Yes	0,08	92,92
5	0,3	51	1	1	739,05	121577	51	1	1	737,99	8410	Yes	-0,14	93,08

Table 7.9: Parameter values for the base simulation.

t_u	τ	τ_r	C_d	C_p	C_c	h	C_o	C_h	η_1	η_2	β_1	β_1	p	N
1	1	0,5	6000	1000	5000	4000	200	50	10	70	3	3	0-0,1-0,3	1-2-5-10-15-20-30

($C_p^*, C_c^*, C_i^*, C_o^*$ and C_d^*), optimal long-run total cost per unit time ($C^*(\theta^*; p, N)$), and demand ($E[d]$ and $\sigma[d]$) are given for various values of N and p.

From the results in the tables, we can see that the long-run total cost per unit time per machine (i.e. the cost-rate) C_M^* for the optimal policy decreases as the number of assets increases, holding p fixed. This relationship is the scale effect, and is to be expected. To consider how the scale effect varies with p, define

$$\lambda(p, N) = \frac{C^*(p, N)/N}{C^*(p, 1)} \tag{7.3}$$

Considering λ (i.e. the cost-rate scale effect) as a function of N for a given p, we would anticipate that λ would decrease as N increases because of the economy of scale in inventory; relative inventory costs will be lower when more assets are considered. We would further anticipate that such a scale effect will be smaller when component heterogeneity is higher (larger p); that is, when component heterogeneity is larger, relatively more assets will be necessary to achieve economy of scale. This relation is indeed what we see in the results represented in Figure 7.8. The effect of component heterogeneity upon the cost-rate scale effect is explained by the fact that greater component heterogeneity implies greater demand heterogeneity ($\sigma[d]$) (Figure 7.8), and this result will imply higher relative inventory costs (relative in the sense of "per asset").

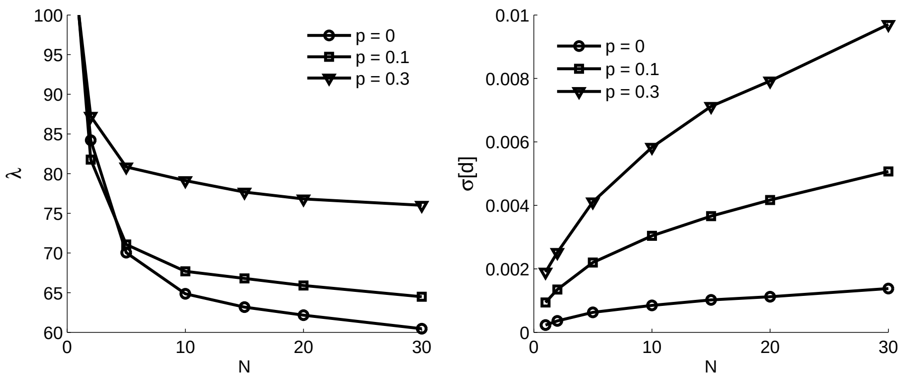


Figure 7.8: (a) Scale effect, λ, as function of the number of assets, N, and proportion of weak components, p. (b) Standard deviation of the demand for spare parts per unit time, $\sigma[d]$, as function of the number of assets, N, and proportion of weak components, p.

Looking at the decision variables $\theta^* = (T^*, R^*, S^*)$ in Table 7.10, it is possible to draw some further conclusions on the joint optimal policy. The preventive

Table 7.10: Optimal policy for parameters defined in Table 7.9 for various N and p.

N	p	T^*	R^*	S^*	C^*	C_p^*	C_c^*	C_i^*	C_o^*	C_d^*	$E[d]$	$\sigma[d]$	C_M^*	λ
1	0	26	17	1	96,95	36,99	10,36	32,51	7,76	9,33	0,03906	0,00023	96,95	100,00
1	0,1	38	5	1	130,44	22,66	34,67	45,58	5,89	21,63	0,02959	0,00078	130,44	100,00
1	0,3	45	3	1	185,68	16,55	72,28	46,89	6,19	43,77	0,03101	0,00144	185,68	100,00
2	0	29	5	1	163,29	65,11	25,16	39,91	13,52	19,58	0,07014	0,00036	81,64	84,21
2	0,1	38	2	1	217,76	45,07	71,02	45,52	11,70	44,45	0,05927	0,00109	108,88	83,47
2	0,3	48	1	1	324,41	29,77	146,59	47,08	11,69	89,28	0,05909	0,00196	162,21	87,36
5	0	31	1	1	339,59	150,51	71,39	41,86	32,55	43,27	0,16478	0,00063	67,92	70,05
5	0,1	37	1	1	468,66	116,84	173,00	42,63	29,50	106,69	0,15144	0,00169	93,73	71,86
5	0,3	46	1	1	745,56	79,60	363,65	42,73	29,11	230,48	0,15233	0,00307	149,11	80,31
10	0	30	1	1	628,86	312,79	134,25	33,56	65,77	82,48	0,33965	0,00085	62,89	64,86
10	0,1	37	1	1	891,63	233,30	345,79	35,86	56,57	220,11	0,30246	0,00246	89,16	68,36
10	0,3	47	1	2	1468,28	153,85	733,94	85,10	52,80	442,60	0,30064	0,00449	146,83	79,08
15	0	30	1	1	918,81	468,50	202,63	26,09	95,68	125,91	0,50904	0,00102	61,25	63,18
15	0,1	36	1	1	1320,08	361,79	511,87	29,35	82,64	334,44	0,46418	0,00289	88,01	67,47
15	0,3	47	1	2	2153,34	230,57	1101,80	77,89	74,08	669,02	0,45093	0,00557	143,56	77,31
20	0	29	1	1	1205,38	649,17	252,98	18,43	126,33	158,47	0,69978	0,00112	60,27	62,16
20	0,1	36	1	2	1739,59	484,64	679,30	69,66	96,32	409,65	0,62051	0,00333	86,98	66,68
20	0,3	47	1	2	2833,80	307,53	1464,88	70,99	92,29	898,11	0,60051	0,00620	141,69	76,31
30	0	29	3	3	1758,57	969,97	383,29	63,78	65,79	275,74	1,04667	0,00138	58,62	60,46
30	0,1	36	1	2	2549,60	725,73	1020,67	55,81	128,11	619,29	0,92987	0,00399	84,99	65,15
30	0,3	47	1	3	4215,11	461,48	2200,92	105,53	120,51	1326,67	0,90166	0,00764	140,50	75,67

replacement age T^* becomes longer as p increases. The reason for this result is that as p increases there is a higher probability of introducing weak components at preventive replacement. This relation results in less maintenance by increasing T^* in the optimal policy. The inventory review period R^* tends to a continuous review policy as N or p or both increase. This result can be explained by the increasing demand variability ($\sigma[d]$) when N or p or both increase. Furthermore, the stock level S^* is quite low. The major reason for the values of R^* and S^* can however be found in the short lead time (τ). Due to the short lead time, it is possible to order spare parts only when they are needed for replacement, as the probability of incurred downtime during the lead time is very small. Moreover, ordering spare parts only when they are needed reduces the costs of inventory significantly. For this reason, S^* is low, as the spare parts in stock are only used to reduce the effect of unplanned or corrective replacement. At the same time, the inventory is reviewed at each time unit ($R^* = 1$) because you want to order spare parts immediately when a demand happens.

Effect of simultaneous deployment on a finite mission time

If assets are simultaneously deployed from new ($T_{i,initial} = 0$), then we might expect the demand process to be initially lumpy as all assets need maintenance at the same time (i.e. higher demand variability $\sigma[d]$). To quantify this effect, we consider simultaneous deployment of assets from new on a finite mission time ($h = 100$). The other simulation parameters are kept as defined in Table 7.9. The results are shown in Table 7.11. Basically, the same conclusions as for the base simulation case in Section 7.3.4 are valid. The optimal policy $\theta^* = (T^*, R^*, S^*)$ for both cases is also similar, although T^* is slightly different to account for the finite time horizon (i.e. it is not optimal to perform preventive replacement at the end of the time horizon). As expected, the demand variability ($\sigma[d]$) for the simultaneous deployment on the finite mission time is much higher than when the long term behavior, as in Section 7.3.4, is considered. However, we might expect that this higher variability in demand results in a higher cost rate C_M^*; this relation is apparently not the case. Again, this situation can be explained by the short lead time, as spare parts are only ordered on demand, and inventory is continuously reviewed. In this way, the higher demand variability is tackled without increasing the cost rate C_M^*. Due to the simultaneous deployment and replacement of assets, the costs of ordering C_o^* are even lower compared to the results in Table 7.10. In the case of simultaneous replacement, the order sizes are bigger, but the number of orders is smaller. As the ordering cost is mathematically independent of the number of spare parts ordered, it is obvious that the costs of ordering decrease.

Table 7.11: Optimal policy for simultaneous deployment on a finite mission time ($h = 100$) for various N, and p.

N	p	T^*	R^*	S^*	C^*	C_p^*	C_c^*	C_i^*	C_o^*	C_d^*	$E[d]$	$\sigma[d]$	C_M^*	λ
1	0	28	20	1	89,58	29,10	11,00	33,14	6,08	10,26	0,03130	0,00336	89,58	100,00
1	0,1	37	6	1	124,71	18,08	34,45	44,37	4,92	22,89	0,02499	0,00659	124,71	100,00
1	0,3	51	1	1	183,10	8,14	75,90	48,86	4,66	45,54	0,02332	0,01155	183,10	100,00
2	0	28	7	1	147,56	57,44	23,30	41,36	10,22	15,24	0,06212	0,00428	73,78	82,37
2	0,1	36	1	1	202,01	36,54	67,80	47,85	8,72	41,10	0,05010	0,00929	101,00	80,99
2	0,3	53	1	1	318,50	15,22	153,00	47,90	8,60	93,78	0,04584	0,01640	159,25	86,97
5	0	26	1	1	290,96	146,12	51,75	46,20	15,48	31,41	0,15650	0,00781	58,19	64,96
5	0,1	34	1	1	430,02	94,99	168,75	45,94	16,57	103,77	0,12876	0,01470	86,00	68,96
5	0,3	51	1	1	742,93	40,31	388,80	45,13	19,99	248,70	0,11813	0,02577	148,59	81,15
10	0	26	1	1	523,83	291,63	103,95	45,34	19,17	63,75	0,31247	0,01028	52,38	58,48
10	0,1	34	1	1	805,89	189,80	332,85	43,51	26,69	213,03	0,25655	0,02173	80,59	64,62
10	0,3	51	1	2	1454,07	103,80	761,80	89,97	38,06	460,44	0,25943	0,02790	145,41	79,41
15	0	26	1	1	757,24	437,13	155,55	44,54	22,67	97,35	0,46835	0,01247	50,48	56,36
15	0,1	34	1	1	1192,31	283,58	501,40	41,22	36,04	330,06	0,38413	0,02683	79,49	63,74
15	0,3	51	1	2	2118,99	121,96	1154,75	85,57	50,11	706,59	0,35299	0,04400	141,27	77,15
20	0	26	1	1	996,93	582,02	211,00	43,64	26,47	133,80	0,62436	0,01484	49,85	55,65
20	0,1	34	1	2	1583,61	380,42	668,55	86,69	44,48	403,47	0,51416	0,03222	79,18	63,49
20	0,3	51	1	2	2799,52	162,70	1537,95	81,39	62,49	954,99	0,47039	0,05248	139,98	76,45
30	0	26	1	1	1467,47	872,86	314,70	42,15	32,92	204,84	0,93627	0,01796	48,92	54,61
30	0,1	34	1	2	2319,34	569,47	1000,50	81,70	59,99	607,68	0,76972	0,03822	77,31	61,99
30	0,3	51	1	3	4141,76	243,91	2298,35	121,62	84,59	1393,29	0,70361	0,06261	138,06	75,40

Effect of lead time

As the lead time τ plays a crucial role in the results presented in the previous sections, we want to determine the effect of this lead time on the joint optimal policy $\theta^* = (T^*, R^*, S^*)$, and its cost rate C_M^* for both the base simulation (case 1), and the simultaneous deployment of assets on a finite horizon (case 2). The lead time τ is changed to a value of 10. The results are summarized in Table 7.12. Most remarkable is the significant increase of S^* in the optimal policy for both cases. The reason for this increase is that, due to the large lead time, it is not possible anymore to order spare parts on demand. The large lead time that has to be bridged increases the probability of corrective replacement and possible downtime of the system during the lead time. Moreover, S^* increases as p increases for the same reason (i.e. higher probability of corrective replacement and corresponding downtime). As expected, the demand variability ($\sigma[d]$) for case 2 is higher than for case 1. However, due to the long lead time, this higher demand variability also has an impact on R^*, and the cost rate C_M^*. To counter the higher demand variability, a continuous review policy is optimal for case 2. This result means R^* is shorter for case 2 compared to case 1, to not miss out on possible demands for spares. Finally, the cost rate C_M^* is lower for case 1. The major reason for this result is the increase in costs of inventory (i.e. high S^*, and short R^*, for case 2) due to the larger demand variability ($\sigma[d]$). This increase clearly shows that, ideally, the joint maintenance and spare parts inventory policy should be adapted to the time since deployment of the assets, and the mission time.

Effect of failure characteristics

As the first objective is to quantify the effect of maintenance quality on a joint maintenance and inventory policy, we quantify the effect of the characteristic life η_1 of the weak components on the optimal policy. The characteristic life η_1 is reduced to 2, which means the quality of the weak components gets worse. The results for both the base simulation (case 1) and the simultaneous deployment of assets on a finite horizon (case 2) are given in Table 7.12. T^* increases for $p \neq 0$ compared to the results of Section 7.3.4 and 7.3.4. This increase is explained by the higher burden (i.e. shorter component lifetime) of introducing a weak component into the system. Finally, the cost rate C_M^* increases for $p \neq 0$ compared to the results of Tables 7.10 and 7.11. This increase is as expected due to the quality decrease of the weak components, which increases the demand. Furthermore, the increase in cost rate C_M^* for case 2 is larger than for case 1.

Table 7.12: Optimal policy for base simulation ($h = 4000$) and simultaneous deployment on a finite mission time ($h = 100$) for various N, p, η_1, and τ.

		$h = 4000$												$h = 100$											
		$\eta_1 = 2$						$\tau = 10$						$\eta_1 = 2$						$\tau = 10$					
N	p	T^*	R^*	S^*	$E[d]$	$\sigma[d]$	C^*_M	T^*	R^*	S^*	$E[d]$	$\sigma[d]$	C^*_M	T^*	R^*	S^*	$E[d]$	$\sigma[d]$	C^*_M	T^*	R^*	S^*	$E[d]$	$\sigma[d]$	C^*_M
1	0	26	17	1	0,04034	0,00020	96,95	25	7	1	0,04034	0,00020	91,39	28	20	1	0,03130	0,00336	89,58	28	20	1	0,03180	0,00384	89,49
1	0,1	39	1	1	0,02872	0,00074	135,05	39	1	1	0,02872	0,00074	153,83	37	1	1	0,02516	0,00717	128,27	35	1	1	0,02554	0,00710	147,25
1	0,3	48	1	1	0,03149	0,00147	197,75	44	3	2	0,03149	0,00147	224,06	54	1	1	0,02483	0,01383	197,44	51	1	2	0,02331	0,01154	223,79
2	0	29	5	1	0,08415	0,00028	81,64	24	11	2	0,08415	0,00028	85,73	28	7	1	0,06212	0,00428	73,78	27	6	2	0,06229	0,00455	83,71
2	0,1	38	1	1	0,06349	0,00107	110,43	35	1	2	0,06349	0,00107	126,97	37	1	1	0,05023	0,01000	104,20	36	1	2	0,05022	0,00941	127,46
2	0,3	50	1	1	0,05641	0,00204	172,51	51	1	2	0,05641	0,00204	195,18	52	1	1	0,05094	0,01986	176,23	53	1	2	0,04641	0,01551	196,26
5	0	31	1	1	0,20894	0,00027	67,92	24	5	3	0,20894	0,00027	73,20	26	1	1	0,15650	0,00781	58,19	26	13	3	0,15555	0,00695	81,96
5	0,1	38	1	1	0,15129	0,00170	95,99	37	4	4	0,15129	0,00170	110,37	34	1	1	0,13099	0,01717	88,61	34	1	3	0,12736	0,01511	120,62
5	0,3	48	1	1	0,15227	0,00305	159,87	46	1	4	0,15227	0,00305	169,32	52	1	1	0,12692	0,03068	166,89	58	1	4	0,11097	0,02521	175,63
10	0	30	1	1	0,38819	0,00062	62,89	26	5	6	0,38819	0,00062	66,39	26	1	1	0,31247	0,01028	52,38	26	1	6	0,31120	0,00980	76,03
10	0,1	36	1	1	0,31749	0,00230	91,42	35	3	6	0,31749	0,00230	100,04	35	1	1	0,25694	0,02396	84,15	35	1	7	0,25208	0,02075	114,76
10	0,3	47	1	2	0,30517	0,00439	156,46	46	2	7	0,30517	0,00439	159,22	50	1	2	0,28582	0,03618	164,50	59	1	7	0,21996	0,03491	168,32
15	0	30	1	1	0,56010	0,00074	61,25	27	5	8	0,56010	0,00074	63,64	26	1	1	0,46835	0,01247	50,48	21	1	9	0,60852	0,00855	74,71
15	0,1	36	1	1	0,47597	0,00280	90,21	35	3	8	0,47597	0,00280	95,72	35	1	2	0,38637	0,02972	109,84	34	1	9	0,38198	0,02705	111,74
15	0,3	48	1	2	0,45072	0,00552	153,60	47	2	9	0,45072	0,00552	154,23	55	1	3	0,36919	0,05455	210,77	55	1	11	0,34092	0,04399	166,79
20	0	29	1	1	0,77410	0,00076	60,27	26	5	11	0,77410	0,00076	61,54	26	1	1	0,62436	0,01484	49,85	18	1	11	0,93791	0,00847	73,88
20	0,1	36	1	2	0,63438	0,00327	89,00	35	3	10	0,63438	0,00327	92,90	35	1	2	0,51524	0,03420	82,38	34	1	12	0,50966	0,03181	109,88
20	0,3	49	1	2	0,60051	0,00616	151,89	47	2	11	0,60051	0,00616	150,82	54	1	4	0,49710	0,06408	158,08	56	1	14	0,45034	0,05222	164,87
30	0	29	3	3	1,12182	0,00108	58,62	27	2	13	1,12182	0,00108	59,77	26	1	1	0,93627	0,01796	48,92	21	1	16	1,21490	0,01136	71,62
30	0,1	36	1	2	0,95107	0,00383	87,08	35	2	13	0,95107	0,00383	89,90	35	1	2	0,77272	0,04316	81,24	34	1	16	0,76337	0,03917	106,68
30	0,3	48	1	3	0,90107	0,00759	150,30	47	2	15	0,90107	0,00759	147,29	54	1	4	0,74191	0,07957	156,18	55	1	21	0,67992	0,06291	162,53

7.3.5 Effect of maintenance quality conclusions

We consider the effect of fleet size on a joint policy of maintenance and spare parts inventory when the quality of spare parts varies. Our model consists of N identical one-component systems (assets) subject to age-based replacement, and with a single echelon periodic review spare-parts policy. In particular, we investigate the effect of spare parts quality (modeled by a mixture with Weibull distributions for the sub-populations) and the size of the fleet on the variability in the demand for spare parts, and consequently upon the optimal policy $\theta^* = (T^*, R^*, S^*)$ and its corresponding long-run total cost per unit time per asset or cost-rate C^*_M. The results show that the cost-rate scale effect (that is the effect of varying the fleet size upon the cost-rate) varies with the quality of spare parts: the poorer the quality of spare parts, the smaller the scale effect. This effect is due to increasing demand variability with poorer component quality. In this way, our approach allows the value in spare parts provisioning for maintenance to be quantified. Furthermore, it is shown that the demand process and corresponding optimal policy for a fleet of identical assets subject to age-based maintenance depends on the size of the fleet, spare part quality, spare part lead time and nature of deployment of the assets.

Future work may consider a predictive maintenance policy or a continuous review policy (r, Q): when the stock level reaches r, order Q. We may also attempt to quantify the sub-optimality of a joint policy that is appropriate for Poisson demand. That is, if the demand were assumed to be Poisson with a rate that corresponds to the demand rate under the exact demand process, and the optimal policy under such Poisson demand were $\theta^P = (T^P, R^P, S^P)$ say, then the objective would be to determine $C(\theta^P)/C(\theta^*) = \phi$, where the cost-rate C in the numerator and the denominator are each calculated using the exact demand process. We might then investigate how ϕ varies with p and N. We might speculate here that again ϕ will increase as N decreases, so that a policy that assumes Poisson demand will be less efficient for smaller N than for larger N. It may also be interesting to consider which inventory policy is best partnered with which maintenance policy. For example, as age-based replacement is arguably a continuous review policy, then it should perhaps be partnered with a continuous review inventory policy. The effect of multiple echelons on scale effects also may be interesting. In short, there are many potential problems to tackle as this is only the first contribution to the field of joint maintenance and inventory policies that considers scale effects while spare parts are of varying quality.

7.4 Conclusions

This chapter presents a literature overview on joint maintenance and inventory models. Based on this literature review major directions for further research are derived, whereof two are addressed in the remainder of this chapter. These are defined as (i) the incorporation of predictive information in joint maintenance and inventory models and (ii) investigation of the effect of maintenance quality on a joint policy. The added value of predictive information in joint maintenance and inventory management is quantified by developing a joint dynamic predictive maintenance and inventory policy for dependent multi-component systems. As such an answer is given to the third research question of this dissertation. Finally, the effect of maintenance quality on a joint preventive maintenance and spare part inventory policy for a fleet of assets is investigated. Detailed conclusions are given in the respective sections of the chapter.

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Chapter 8

Conclusions

8.1 Conclusions linked to research questions

Recently, new technologies (e.g. diagnostics, prognostics and e-maintenance) have been emerging which possess the potential to reduce maintenance costs and increase maintenance efficiency and effectiveness. However, it is clear that the evolution of maintenance is not solely based on technical but rather on techno-economic considerations. The right maintenance decision making structure should be in place to fully exploit the potential of these new technologies. Therefore, the aim of this dissertation was to develop an information-based maintenance methodology with focus on predictive maintenance policy development and corresponding performance determination and optimization. Where information-based maintenance is defined as: (Muller et al. 2008)

> *"The overall concept of information-based maintenance is that of updating decisions for inspection, repair, and maintenance scheduling based on evolving knowledge of operation history and anticipated usage of the machinery, as well as the physics and dynamics of material degradation in critical components."*

Hence, a detailed study on the business economics related to the implementation of an information-based/predictive maintenance policy has been performed by answering three defined research questions. These are defined by considering the major flaws in maintenance management and optimization, which can be summarized as follows: (i) development of predictive maintenance decision support tools and models, (ii) literature urges for a need for more application based maintenance optimization, (iii) the limited scope with regard to maintenance objectives and criteria and (iv) availability of maintenance data. Furthermore, the research within this dissertation has been performed within the scope of: (i) maintenance management for physical assets and (ii) predictive maintenance performance evaluation and optimization without development of condition monitoring or prognostic tools and models. The research questions are formulated as follows:

> **First research question**: How to determine and prioritize business specific maintenance objectives which can be used for maintenance performance measurement (MPM), management and optimization?
>
> **Second research question**: Determine the added value of predictive information on component degradation in the form of remaining useful life (i.e. information-based) in maintenance decision making by developing and optimizing a dynamic predictive maintenance policy (PdM) for complex multi-component systems that can be used for both long-term performance evaluation of PdM, as for real-time and dynamic maintenance decision making.
>
> **Third research question**: How and how much value will predictive maintenance generate in the entire value chain, specifically looking to inventory management?

The first research goal addresses the limited scope of maintenance objectives in maintenance management. This led to the development of a comprehensive methodology, based on the analytic network process (ANP), to determine and prioritize business specific maintenance objectives and corresponding maintenance performance indicators (MPI) from a generic maintenance objective network (Chapter 3). Moreover, it is shown that the developed model has a wider applicability within maintenance performance measurement, rather then only selection of business specific maintenance objectives. Therefore, a maintenance performance measurement (MPM) framework is presented that addresses the two major flaws (i.e. alignment with the organizational strategy and lack of an agreed-upon methodological approach of deriving business specific MPI) within currently available MPM frameworks. By considering all organizational levels (i.e. strategic, tactical and operational level) corporate as well as operational maintenance objectives and corresponding MPI are defined. The development of the MPM system and ANP model aligns the maintenance objectives on all management levels with the relevant MPI used. It supports maintenance managers in translating maintenance objectives to relevant MPI, starting at the operational level and aggregating these to form MPI at the corporate level in order to create value for the entire organization. In this way the defined MPI are aligned with the organizational structure of the company. The result is a business specific MPM system usable throughout the entire company. Moreover, the derived maintenance objectives can be used for maintenance optimization purposes. The methodology is illustrated and validated by the application to five extensive case studies. The results of these case studies endorse the importance of customization of the implemented MPM system to fit the specific business environment. Furthermore, they illustrate the importance of a methodological approach to select business specific MPI based on the specific maintenance objectives and corporate strategy.

Chapters 4, 5 and 6 address the second research question by presenting models for the optimization and added value quantification of predictive maintenance. Predictive maintenance models for long-term performance evaluation (Chapter 4), real-time and dynamic decision making (Chapter 5) and a combination of both (Chapter 6) are developed.

Chapter 4 presents a model for long-term performance evaluation of predictive maintenance wherein a new approach to model the performance of a condition monitoring system (CMS) is considered. Furthermore, the effect of secondary damage accumulation is taken into account. The methodology is illustrated by an extensive case study on a wind turbine gearbox. This case study shows the added value of implementing a CMS into the gearbox compared to the currently applied maintenance strategy. Moreover, the analysis clearly indicates that the performance of the CMS has a major influence on the generated added value. It is shown that the performance of the CMS and possible secondary damage should be taken into account in order to draw the right conclusions on the real economic value. Note that the scope of the presented model is limited to assist maintenance decision makers in a long-term investment decision. Therefore, when the decision to implement a CMS is made, other models are necessary to make dynamic real time decisions based on the condition monitoring and corresponding predictive information on component degradation. Consequently, Chapter 5 presents predictive maintenance models for real-time and dynamic maintenance decision making. The developed models are applied to three case studies in order to illustrate their applicability in real-life case studies. The first two models (i.e. packaging machine and photocopiers) address the trade-off between maintenance cost and product quality degradation cost. Based on the developed profit maximization technique, it is possible to optimize maintenance in real-time by monitoring the degradation of the end product. It is shown that the added value of the predictive information in maintenance scheduling and optimization regarding the trade-off between maintenance cost and quality degradation cost is substantial. The third case study extends the use of condition monitoring from purely avoiding failures and scheduling maintenance to production capacity optimization. Temperature monitoring is used to optimize production capacity in wire process industry. The use of predictive information shows major potential to increase production capacity, however, the proposed model still needs to be validated in the real production plant before final conclusions can be drawn. Finally, it can be concluded that for certain applications predictive maintenance optimization should not only take into account the health of the machines and components, but should also include final product quality and production capacity as optimization parameters. Note that it is not always straightforward to determine the long-term performance, as the presented models depend on real-time data that is often censored due to the execution of maintenance or not available for long time periods. Finally, the developed models in Chapter 5 do not address interactions between components or systems as they only consider single-component and single-system applications.

As indicated, both type of models developed in Chapters 4 and 5 have their limitations. Therefore, based on the understanding gained from the models developed in Chapters 4 and 5, an answer to the second research question of this dissertation is given in Chapter 6. Consequently, this chapter presents a dynamic predictive maintenance policy (PdM) for complex multi-component systems that minimizes the long-term mean maintenance cost per unit time, while considering different component dependencies (i.e. economic, structural and stochastic dependence), that can be used for both long-term performance evaluation of PdM, as for real-time and dynamic maintenance decision making. Predictive information is dynamically included into the presented maintenance policy in order to schedule maintenance in an optimal way. The maintenance schedule is updated when new (short-term) information on the degradation (e.g. by inspection) and remaining useful life of components becomes available. Furthermore, economic, structural and stochastic component dependencies are considered to optimally group and schedule maintenance activities. The results show significant cost savings for the presented dynamic predictive maintenance policy, as the policy is able to dynamically react to changing component deterioration and dependencies within multi-component systems. Furthermore, the magnitude of these savings depends on the component interactions present in the system, which clearly illustrates the importance to include these interactions in the maintenance decision problem. By doing so, the dynamic predictive maintenance policy assures an optimal maintenance policy all of the time rather than only over time.

An answer to the third research question is formulated in Chapter 7 by investigating joint maintenance and inventory models. Based on an extensive literature review major directions for further research are derived, whereof two are specifically addressed. These are defined as (i) the incorporation of predictive information in joint maintenance and inventory models and (ii) investigation of the effect of maintenance quality on a joint policy. The added value of predictive information in joint maintenance and inventory management is quantified by developing a joint dynamic predictive maintenance and inventory policy for multi-component systems considering different levels of dependence (i.e. economic and structural). The joint policy optimizes both maintenance and inventory parameters while minimizing the long-term average maintenance and inventory cost per unit time. The results show that the developed joint predictive maintenance and inventory policy reduces the long-term total (i.e. maintenance and inventory) costs for both multi-component systems without dependence and multi-component systems with dependence. It is clear that predictive information can provide additional value in joint models. For systems without dependence both the maintenance cost and inventory cost decrease due to the better predictability of spare part demand based on the predictive information. For systems with dependence the conclusions are slightly different. The total cost decreases when the dependence increases (i.e. due to grouping of maintenance activities). But due to the adopted sequential optimization approach the optimal maintenance schedule determines the inventory decisions, which leads to an increasing inventory cost when the dependence between the components increases. This means that all advantages of the predictive information for dependent multi-component systems are reflected in the maintenance costs, rather than in the inventory costs. Consequently, the structure of the system (i.e. component dependencies) has a major influence on the generated added value. The presented results indicate that a real joint optimization, opposed to the proposed sequential; of the maintenance and inventory decisions has the potential to reduce the costs even further, especially for dependent multi-component systems. Furthermore, as opposed to the perception in most of the publications, where the use of predictive information is perceived to reduce inventory costs due to the better predictability of spare part demand, the availability of this predictive information does not guarantee a decrease in inventory costs in multi-component systems with dependence. It is shown that both maintenance and inventory policy have to be adjusted to each other to fully exploit the benefits of predictive information in a joint policy for dependent multi-component systems.

8.2 Research contributions

This dissertation presents both academic and industrial contributions. The developed models contribute to the academic research and state-of-the-art without forgetting their industrial applicability, as most of the models are applied to real-life case studies. The bulleted list below discusses the research contributions as pertaining to the developed models within the frame of this dissertation.

- Maintenance objective selection and performance measurement
  - A methodology based on the analytic network process (ANP) for maintenance objective selection and prioritization is developed. The model directly addresses the limited scope of maintenance objectives in maintenance management.
  - A maintenance performance measurement (MPM) methodology is presented that addresses both the lack of alignment with the organizational structure and the lack of a methodological approach to derive business specific maintenance performance indicators (MPI) within currently available models.
- Predictive maintenance performance evaluation and optimization
  - A significant contribution to the development of models for the economic justification of predictive maintenance is made in this dissertation. Predictive maintenance models for long-term performance evaluation, real-time and dynamic decision making and a combination of both are developed. These models provide maintenance decision support in order to take cost-effective decisions based on predictive information. Moreover, they provide sound business insight for the justification of PdM and as such assist to determine the cases in which PdM is expected to be very beneficial, beneficial, neutral or possibly too expensive.
  - The state-of-the-art on multi-component maintenance scheduling is advanced by including: (i) predictive information on component degradation in the form of remaining useful life (RUL) (ii) all types of component dependence (i.e. economic, structural and stochastic dependence) (iii) the impact of partial dependence on the optimal policy and (iv) complex systems with non-zero maintenance downtimes, random component failure thresholds and imperfect maintenance.
  - A new approach to model the performance of a condition monitoring system (CMS) and related secondary damage accumulation is presented. Moreover, the model is applied to a specific case study of a wind turbine gearbox to illustrate its applicability in real-life case studies.
  - An initial contribution is made towards the development of models for real-time maintenance decision making based on predictive information on component degradation, where product quality and production capacity are introduced in the maintenance optimization problem.

- Joint maintenance and inventory policies
  - To the best of the author's knowledge this research presents a first contribution towards the development of a joint dynamic predictive maintenance and inventory policy for multi-component systems with dependence. The presented model enables one to determine the value of predictive maintenance information with regard to inventory management.
  - The effect of spare part and maintenance quality, fleet size and nature of deployment of the assets on a joint policy of maintenance and spare parts inventory is investigated. In particular, the effect on the variability in the demand for spare parts, and consequently upon the optimal policy and its corresponding long-run total cost per unit time per asset are considered. Hence, the presented approach allows the value in spare parts provisioning for maintenance to be quantified.
- General problems in maintenance management
  - The models developed within this dissertation can help to solve the maintenance data problem, as they can assist in determining the important data that are necessary in specific cases, reduce uncertainty about some parameters and avoid time loss by gathering irrelevant data. The models have the capability to provide the maintenance decision maker with the right information at the right time to make the right decision. Moreover, models with different data requirements (e.g. condition monitoring data necessary or not) are developed, which means that based on the available maintenance data and purpose (i.e. take investment decision or real-time decision making based on available data) another model can be used for decision making.
  - The scope of the commonly available maintenance optimization models and the considered maintenance objectives is extended by including product quality, production capacity, availability, downtime, maintenance cost and inventory cost as maintenance objectives into the maintenance decision problem.
  - The performed research significantly contributes to the development of application based maintenance optimization by presenting several real-life case studies. As such the developed models proved to be able to deal with real data from industrial cases. In this way one of the major issues in maintenance management, applicability of the developed models in real-life problems is clearly addressed.

8.3 Outlook

Several directions for further research can be derived based on the contributions made within this dissertation. These can be defined as follows:

- **Benchmarking purposes** - The developed ANP methodology is usable as a comparison tool between different business sectors and environments, which makes benchmarking between and within different business environments possible.

- **E-maintenance for maintenance performance measurement** - It could be interesting to investigate how the concept of e-maintenance can assist with the implementation of a maintenance performance measurement (MPM) system and the measurement of maintenance performance indicators (MPI).

- **Component and system dependencies** - Different system structures can be investigated as the developed models are limited to series systems. Changing the system structure will affect the component dependencies. Moreover, looking into different methods to model stochastic dependence could be interesting as the focus in this dissertation is mainly on economic and structural dependence. Finally, the models can be extended to multiple multi-component systems to include system dependencies. All these extensions can be implemented by changing the dependency relations in the model presented in Chapter 6. For example, an initial study for two multi-component systems is already made in Van Horenbeek et al. (2012).

- **Incorporation of maintenance and/or spare part quality into a joint predictive maintenance and inventory policy** - Within this dissertation two models considering joint maintenance and inventory are developed: (i) a joint predictive maintenance and inventory policy and (ii) a joint age-based maintenance and inventory policy considering maintenance quality for a fleet of assets. Both models could be combined in order to determine the effect of maintenance and/or spare part quality in a joint predictive maintenance and inventory policy. One could expect that due to the availability of component degradation information a badly executed maintenance action or poor quality spare part is identified in an early stage. In this way the predictive information can possibly generate additional value by avoiding early failures.

- **Inclusion of production schedules** - The focus in this dissertation is on the connection between maintenance and inventory. However, the production schedule also has an influence on both maintenance and inventory. Therefore, it could be interesting to investigate the added value of predictive information in a joint maintenance, inventory and production policy.

- **Maintenance service contracts and business models** - With the use of Internet, web-enabled and wireless communication technology, e-maintenance is transforming manufacturing companies to a service business to support their customers anywhere and anytime (Lee et al. 2006; Muller et al. 2008). Therefore, opportunities for the development of new maintenance business models arise by the implementation of e-maintenance and predictive maintenance (PdM). An initial contribution with regard to the development of maintenance service contracts and business models is already made in Van Horenbeek et al. (2013c).

- **Develop a case study for the developed information-based maintenance methodology** - It would be interesting to develop a case study wherein all steps of the developed information-based methodology within this dissertation are applied. These different steps would be: (i) select business specific maintenance objectives (Chapter 3), (ii) determine the performance and optimize a predictive maintenance policy according to the selected maintenance objectives by applying the models developed in Chapters 4 - 6 and (iii) include inventory management into the optimization problem (Chapter 7). Note that this would be a huge challenge, mainly because of data availability.

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Curriculum vitae

October 8th, 1986	Born in Leuven, Belgium

Education

1998-2004	Sciences and Mathematics Heilige-Drievuldigheidscollege, Leuven
2004-2008	Master of Industrial Sciences Specialization Electromechanical Engineering GroepT Leuven
2008-2009	Master of Industrial Management Specialization Product and Production Management KU Leuven
2009-present	Research Assistant and PhD student KU Leuven, Faculty of Engineering, Department of Mechanical Engineering, Centre for Industrial Management.

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- **RAMS 2013 - T. L. Fagan Best Student Paper Award** for the paper: Van Horenbeek, A., Pintelon, L. (2013). A prognostic maintenance policy – effect on component lifetimes. In proceedings of the Reliability and Maintainability Symposium (RAMS 2013). Orlando, US, January 2013 (pp. 148-153).
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- **MPMM 2013 - Best Paper Award** for the paper: Chemweno, P., Pintelon, L., Van Horenbeek, A. (2013). Asset maintenance maturity model as a structured guide to maintenance process maturity. In proceedings of the 3rd MPMM (Maintenance Performance Measurement and Management) conference. Lappeenranta, Finland , September, 2013 (pp. 58-70).

FACULTY OF ENGINEERING SCIENCE
DEPARTMENT OF MECHANICAL ENGINEERING
CENTRE FOR INDUSTRIAL MANAGEMENT
Kasteelpark Arenberg 1
B-3001 Heverlee
adriaan.vanhorenbeek@cib.kuleuven.be